Cognitive-Technology Implementations’ Transformative Dynamics

Socio-Technical Implications for Knowledge-Intensive Work in the Financial-Accounting Domain

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The rise of cognitive technologies such as artificial intelligence (AI) with learning capacity and of advanced rule-based automation systems have in recent years called humans’ dominance in the domain of cognitively oriented knowledge-intensive work into question. Proliferation of cognitive technologies, propelled by rapidly expanding interest in applying AI to such knowledge work, has opened a wide spectrum of AI development and implementation projects, with the variety and quantity of cognitive-technology initiatives ballooning accordingly. Therefore, AI’s presence in knowledge-work organizations is growing. As it comes to rival rule-based automation systems (which follow a set of premeditated steps), the application of AI is enabling both automation and augmentation of a broader range of work tasks, thanks to capabilities of learning. Novel cognitive technologies facilitate offloading of repetitive tasks, even highly complex ones, via automation that presents possible solutions to the particular task at hand; furthermore, they can stimulate insight into the work through the information with which they augment humans’ decision-making. However, organizations need to tread carefully when deploying these technologies: alongside beneficial humanistic and instrumental outcomes, such technologies can lead to disruptive dynamics that may produce detrimental outcomes for individuals and organizations alike, such as deskilling of the overall socio-technical system.

Responding to these concerns, three qualitative studies were conducted to enrich socio-technical research related to cognitive-technology implementations’ implications for knowledge intensive work. Essay 1 examines the transition toward human–AI work and the subsequent transformation of practices through shifts in routines’ dynamics and changes in work roles. Essay 2, in turn, examines negative elements: how exploiting cognitive automation encourages erosion of knowledge workers’ skills and the effects of this skill erosion at the level of organizations, and the third essay explores why AI system development and deployment projects face delays and complications. The research deepens understanding of the evolving dynamics among the practices employed in these systems’ development and implementation.

By addressing key phenomena linked to these phenomena, the dissertation contributes to both theory- and practice-oriented work on topical issues of developing and implementing cognitive technologies for utilization in knowledge-intensive work processes. Offering insight as to the patterns that can lead to beneficial/detrimental outcomes, the research serves the aim of expanding understanding of cognitive technology’s socio-technical implications.
Tekijä
Joona Ruissalo

Väitöskirjan nimi
Kognitiivisten teknologioiden käyttöönottotojen transformatiiviset dynamiikat: Sosiotekniset vaikutukset tietointensiiviseen työön taloushallinnon alalla

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Artikkeli

Tiivistelmä
Kognitiivisten teknologioiden, kuten oppimiskyysen tekoälyn ja kehittyneiden sääntöpohjaisten automaatiojärjestelmien, nopea kehittyminen viime vuosina on alkanut haastamaan ihmisen pääasiallista ja hallitsevaa roolia tietointensiiviseen työn suorittamisessa. Koska uusien kognitiivisten teknologioiden hyödyntäminen on tullut mahdolliseksi monissa työtehtävissä, samalla myös kiinnostus näitä teknologioita kohtaan on kasvanut nopeasti ja se on johtanut erityisesti erilaisten tekoälyn kehitys- ja käyttöönottoprojektien määrän ja monipuolisuuden laajaleiseen kasvuun. Näin ollen tekoälyyn pohjautuvat ratkaisut ovat tehneet mahdolliseksi myös oppivien järjestelmien kehittämisen sääntöpohjaisten automaatiojärjestelmien lisäksi, mikä ovat perustuneet ennalta määriteltyjen vaiheiden automatisointiin. Tekoälyn käyttö puolestaan mahdollistaa useampien työtehtävien automatisoinnin ja augmentaation johtuen sen kysynnä oppia toimintamalleja käyttössä olevan datan pohjalta. Nämä kognitiiviset teknologiat tarjoavat organisaatiolle uusia ja houkuttelevia tapoja parantaa niiden tehokkuutta ja tuottavuutta, koska algoritmit voivat käsittää dataa ja informaatiota nopeasti sekä vähentää inhimillisiä virheitä työprosesseissa, näin ollen parantaa organisaatioiden yleistä suorituskykyä. Organisaatioissa on kuitenkin toimittava varovaisesti näitä teknologioita käyttöönotettaessa, sillä tavoiteltuja hyötyjä ei välttämättä saavuteta, vaan liiallinen nojauminen uusien teknologioiden käyttöön voi johtaa odottamattomiin ja haitallisii seurauksiin, kuten taitojen rapautumiseen niin yksilö- kuin kollektiivisella tasolla.


Kaiken kaikkiaan tämä väitöskirja tarjoaa niin teoreettisia kuin käytännön löydöksiä kolmen laadullisen tutkimustyön pohjalta käsitellä ajankohtaisia teemoja liittyen kognitiivisten teknologioiden kehitykseen ja käyttöönottoon tietointensiivisiin työprosesseihin. Näin ollen väitöskirja tarjoaa uutta tietoa kognitiivisten teknologioiden käyttöönottojen liikkeelle laittamien dynamiikkojen muuntumisesta, laajentaen ymmärrystä niiden sosiotekniisistä vaikutuksista

Avainsanat
kognitiiviset teknologiat, automaatio, augmentaatio, sosiotekniikka, muutos, tietointensiivinen työ, taloushallintotutkimus

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The journey and its people

When my doctoral studies began back in September 2019, little did I know what the coming years would bring. As I embarked on an ambitious longitudinal research project only a few months after that, I could not have expected that less than two months later the face-to-face interviews would be suspended amid pandemic-prompted mandates for minimal co-located social interaction. Obviously, the switch to fully remote work more broadly required adaptation on multiple fronts: virtual meetings, conferences held in virtual form, and remote teaching of doctoral courses could not be the same as physical presence in those situations, meeting new people, etc. These shifts turned out to mirror some aspects of the adjustment phenomena my doctoral research ended up exploring.

Another shift followed. As the world started gradually reopening its doors, in early 2022, a research visit to present my doctoral research at Paris’s IÉSEG School of Management and ESSEC Business School, suggested and arranged by my supervisor Esko Penttinen, unlocked the academic world for me in a totally new way, and I again felt part of a larger community rather than rooted to a home office. Ever since, through insightful and rewarding discussions at work facilities, seminars, and conferences, I have been privileged to discover and work with many inspiring people. As I grew to challenge myself intellectually and push my limits over this eventful four years, I emerged at the far end extremely grateful to everyone who helped me, in whatever unique way, to weather the difficult times and with whom I could share the good times. I want to thank all who helped me along the four-year journey.

Humanistic support

While this accomplishment has been shaped by support and guidance from numerous magnificent people, my thanks extend first and foremost to my supervisors: professors Esko Penttinen and Aleksandre Asatiani. I consider myself fortunate to have been able to work with both of you ever since commencing work on my master’s thesis in 2016, and I still remember the discussion at the old Helsinki campus when you asked about my interest in applying to Aalto University’s doctoral program. Had you not raised this possibility, I might never have traveled this path. I am glad you did.

Esko, your guidance and support have proven invaluable for learning how to navigate the academic world. Your encouraging, proactive approach created an environment that made it easy to build my capabilities and confidence as a researcher. Whenever an aspect of research puzzled me or I faced a simple practical issue, you were available. By taking the time to address my questions, you helped immensely to alleviate the uncertainties along the path of pursuing a PhD degree. Furthermore, the research efforts that I have undertaken would have
been impossible without your active involvement in creating the opportunities to talk to the right people and, thereby, enabling research collaboration to form. Beyond your supervision and project management, I am grateful also for your co-authorship contribution, which has provided perspective and insight into conducting rigorous research.

Aleksandre, thank you for taking the time to guide me and offer insight at crucial points in my doctoral studies. Your positive attitude, along with the determination you have shown during work on joint research papers, has not only helped me to learn the tools of the trade but also fostered the right mindset for approaching research work with confidence. Your incisive yet kind comments and feedback over the years have helped push my work forward. It has been a true pleasure to work with you.

Alongside my supervisors, I have had several other genuinely amazing people as co-authors in research-paper projects. I consider myself fortunate to have had the opportunity to collaborate with Prof. Tapani Rinta-Kahila, Senior University Lecturer Antti Salovaara, Prof. Wael Soliman, and most recently Prof. Reza Mousavi Baygi. Working as a co-author of Tapani, Antti, and Wael helped me understand what it takes to publish a paper in a top-level journal early in my career, a process that revealed much during my doctoral studies. Working on this project with such talented and deeply insightful individuals has been an invaluable learning experience that has tremendously improved my skills as a researcher – I cannot thank you enough for this opportunity. Reza, thank you for hosting me at IESÉG when I first presented my work there and then hosting me again for my two-month research visit. Although our shared time in Paris was cut short on account of your Vrije Universiteit Amsterdam appointment, that time still let us work through my issues with the research-paper project and rapidly find ways to overcome several issues through productive discussion. I am glad you decided to step aboard for the ongoing paper project and share your expertise with the team. I look forward to continuing to work with you.

The support that I have received over the years from my colleagues at Aalto University has had a significant impact on the trajectory of my journey. I am grateful to Prof. Virpi Tuunainen and Prof. Matti Rossi for giving me varied opportunities to improve as a junior scholar, Dr. Kari Koskinen for the possibility to learn how to arrange and deliver teaching, Dr. Juri Matinheikki for eye-opening insight related to the world of academia, and all the rest of the faculty’s personnel for the feedback on my work at department seminars – but also for lunchtime conversations on a broad range of stimulating and immensely interesting topics. These thanks could never be complete without mention of my doctoral-studies peers. The journey would not have been the same if the experiences, both good and bad, could not have been shared. All the great conversations have been of value, but I want to thank especially my closest peers Sampsa Suivivu, Misa Bakajic, and Dr. Marta Malik, for the discussions, great ideas, and advice over the years. Along similar lines, I extend my gratitude to the ICIS 2022 Doctoral Consortium participants, mentors, and organizers for an outstanding three-day event. Special thanks go to my group members Haoyue Gu, Laura Kochendörfer, Mylène Struijk, Roxanne Llamzon, and Sambit Tripathi for co-creating an amazing skit that hit the bull’s eye.

Such reminders that such a journey cannot be all work point to the final group I want to thank: my family and friends outside academia. In particular, I want to thank my partner, Laura, for having been there for me at every turn on this journey at my side. It is hard to describe how much you have helped me via, in addition to unforgettable moments shared for eight years already, the last four years of sharing the burden at times of doubt and reassuring
me of my conviction to follow this path when the uncertainties and perplexities every so often tempted me to stray from it. Lastly, I am deeply grateful to my parents for a compassionate upbringing that granted me a strong moral compass for navigating whatever situations I might face in life, to my grandparents for their grounding wisdom, and to my siblings for sharing the fun times and helping create memories that we can cherish.

**Instrumental support**

Throughout the dissertation project, I benefited from the generosity of the HSE Foundation, Jenny and Antti Wihuri Foundation, Kaute Foundation, and Matti Lehti fund. Therefore, I thank you deeply for enabling this project. You provided the financial support needed for carrying out the research and completing the finished dissertation.

Secondly, the project would not have been possible without access. I wish to express my gratitude to the case-company managers and directors who granted me the opportunity to conduct interviews all the way from January 2020 to June 2023 with accountants and various other experts. For all those who participated in the interviews over the course of the project, I know that the questions were not always easy to answer, but I have been unwaveringly impressed by the dedication shown. You answered as thoroughly as possible and shared your experiences even with difficult situations. Without your commitment to participating openly and frankly, my work would have been completely different from what it was able to become. It could never have reached this level of depth and breadth without you. You can take pride in the work you do, in that as you perform all your day-to-day work duties you stand at the cutting edge of socio-technical change. It takes tremendous effort to adapt to such change and keep striving for high-quality work results.

With the resulting dissertation now written, I want to thank the pre-examiners – Prof. Andrew Burton-Jones, from the University of Queensland, and Prof. Henri Pirkkalainen, at Tampere University – for insightful comments and feedback that helped enrich my perspective and thus further improve my work. Furthermore, it is an honor to have Professor Burton-Jones as the official opponent for my public defense, and I look forward to the debate.

**The path ahead**

Before I embarked on this journey, the quest to undertake such a project and produce an entire dissertation seemed like a Herculean effort. However, by taking the path step by step through all its many twists and turns and with the gentle nudging of the people around me to guide me toward the right direction, I finally reached this milestone. As with any milestone, this is a landmark but also a waypoint – there are several more mile markers to come, on the path yet to be traveled. Whatever turns I take at each of its crossroads, I will remain curious. Hence, I will keep exploring how we as humans shape our technologies and how they, in turn, transform us.

With those thoughts in mind, I will end with a quote from Heraclitus with a core message that captures the essence of both my personal journey and the research I have carried out: “No man ever steps in the same river twice, for it’s not the same river and he’s not the same man.”

Helsinki, July 7, 2023
Joona Ruissalo
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List of Essays

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2. Rinta-Kahila, Tapani; Penttinen, Esko; Salovaara, Antti; Soliman, Wael; Ruissalo, Joona. The Vicious Circles of Skill Erosion: A Case Study of Cognitive Automation. Accepted for publication, Journal of the Association for Information Systems.

The Author’s Contribution

Essay 1: Transition to Human–AI Work: Shifts in Routines’ Dynamics and the Implications for Roles in Knowledge-Intensive Work

Ruissalo was the sole author of Essay 1.

Essay 2: The Vicious Circles of Skill Erosion: A Case Study of Cognitive Automation

Rinta-Kahila was the lead author of the second paper. Penttinen identified the research context via my collection of data for a separate project and proposed studying the topic to Rinta-Kahila, who developed the data-collection instrument and theoretical framing accordingly with assistance from Penttinen and Salovaara. The pre-existing project supplied the first-round data for the paper, and Rinta-Kahila and Penttinen collected further data together, with Rinta-Kahila then performing the primary analysis and me handling the secondary analysis. Rinta-Kahila wrote the paper under Penttinen’s guidance. Soliman provided fine-tuning for the theoretical framing and contributed to the positioning of the results relative to other scholarly work. He and Salovaara contributed to enhancing both the research and the paper’s reporting on it. Ruissalo wrote the section on the two applicability checks that Penttinen and Ruissalo had conducted with practitioners (in two sessions using material that I created jointly with Rinta-Kahila) to verify the theory-based model.

Essay 3: Fluid Socio-Technical (Trans)formation of an AI System

For the final paper, Ruissalo was the lead author. Ruissalo proposed the overall idea to Penttinen, who articulated the research problem. Penttinen, Asatiani, and Ruissalo together prepared the paper’s introduction; Asatiani wrote the first part of the literature review and Ruissalo the latter portion; and also Ruissalo performed the data analysis and wrote the rest of the paper under the guidance of Penttinen and Asatiani, who contributed to the positioning of the results in relation to prior research.
Part I: Synthesis
1. Introduction

Cognitive technologies such as advanced rule-based systems for tasks’ automation and, going further, artificial-intelligence (AI) systems capable of learning (Davenport & Ronanki, 2018) have in recent years come to challenge humans’ dominance in various domains. Together, the proliferation of cognitively oriented technologies and rapid growth in interest in applying them for settings of knowledge-intensive work have prompted a plethora of AI development and implementation projects for cognitive work in such settings. In a feedback loop, the vast breadth of their application has driven up the variety and number of cognitive-technology development and implementation initiatives (Davenport & Ronanki, 2018). Because the landscape features not only rule-based automation (whereby a system takes a set of premeditated steps) but also increasing prevalence of AI implementations, these systems’ profile is growing at knowledge-work organizations, where their learning abilities afford automating and augmenting a broader and broader spectrum of work tasks. Since these cognitive technologies both permit offloading of repetitive and even complex tasks (through automation) and represent potential solutions for given tasks while also affording insight into the work by informing the people involved (thus augmenting human decision-making) (Rai, Constantinides, & Sarker, 2019; von Krogh, 2018), they hold special appeal as novel ways for business managers to increase organizations’ efficiency – in that algorithms can process data and information more quickly – and to reduce human error in the work processes simultaneously (Lacity & Willcocks, 2016). Therefore, they and the models involved appear promising for improving operations’ performance overall (Asatiani et al., 2021).

Because the cognitive effort of a human carrying out knowledge-intensive tasks can be replaced via automation and/or complemented by technologies’ augmentative capabilities (Raisch & Krakowski, 2021), the systems create prospects for human–AI hybrid work (Lyytinen, Nickerson, & King, 2020; Rai et al., 2019) wherein cognitive technology and humans dynamically function in combination as a unit (Rai et al., 2019). However, this is far from straightforward: introducing cognitive technology to a knowledge-intensive work process precipitates a shift in the socio-technical system’s dynamics, with the resulting changes in work practices possibly leading to work-role changes that reshape what is required for the individuals to carry out the assigned or necessary tasks (Davis & Hufnagel, 2007). These changes can usher in performance gains, profit increases, and cost savings for the organization (Asatiani et al., 2021; Strich, Mayer, & Fiedler, 2021) at least in the short term. In parallel, as Davis and Hufnagel (2007) have pointed out, some groups welcome them since individuals too might benefit, through enhanced career prospects and more meaningful work.

The mechanism by which cognitive technologies’ introduction to an organization can yield instrumentally and humanistically beneficial outcomes (Sarker, Chatterjee, Xiao, & Elbanna,
in combination is redivision of work as the technology takes over specific tasks. In connection with this process, which some scholars conceptualize as adaptation of both ostensive and performative aspects of routines (Feldman & Pentland, 2003), one can view routines as generative systems that create stability and shifts alike (Feldman & Pentland, 2003). Such a model accentuates how work practices’ alteration sets in motion the transformation of work roles as responsibilities evolve in tandem with the work tasks themselves (Black, Carlile, & Repenning, 2004). Intentional reskilling is a crucial element of adjustment to the new skill requirements that arise as human knowledge workers’ practices and roles transform in the evolution of human–AI work, ensuring that humans and their organizations retain expertise consistent with the skillsets needed in the midst of the transformation (Davenport & Kirby, 2016; McGuinness, Pouliakas, & Redmond, 2019). For this, organizations must understand how the shifts in dynamics are influencing what is required and grasp how knowledge workers, by exploiting “know-what” and “know-how” acquired through formal learning and “learning-by-doing” over the years, make use of specific skills and capabilities to complete a wide array of tasks in their specific work domain. Another important factor is that experiences of the intended and actual consequences of such gradually unfolding transformations hinge on the work roles (Davis & Hufnagel, 2007), since the extent to which any given cognitive technology can be applied varies with the tasks’ specifics. Moreover, as Davis and Hufnagel (2007) have noted, high-level focus on improving efficiency by means of a cognitive-technology system can obscure the work processes of human experts further, causing cognitive dissonance when, for instance, the work’s design under the new system runs counter to their profession’s code of conduct.

Since humanistic and instrumental benefits are not the only possible outcomes, organizations need to tread carefully when bringing cognitive technologies into use. Disruptive dynamics percolating through a socio-technical system in response to such technologies can lead to detrimental developments over time. Unintended consequences of implementing and expanding the use of such technology can come hand in hand with the intended consequences (Ash, Berg, & Coiera, 2004; Jussupow, Spohrer, Heinzl, & Gawlitza, 2021). While humans often retain responsibility and oversight over algorithmic outputs when forming dynamically functioning units in human–AI work, this safeguard does not prevent excessive reliance on algorithmic decision-making and, thereby, deskilling (Arnold & Sutton, 1998; Strich et al., 2021). It can occur even among humans who know that offloading manual tasks to cognitive technologies in pursuit of greater efficiency and less burdensome tasks may involve gradually decreasing involvement – to the point where they have little or no involvement in drawing inferences or critically assessing the algorithms’ outputs. Studies in knowledge-work domains such as auditing (Sutton, Arnold, & Holt, 2018) and finance (Mayer, Strich, & Fiedler, 2020; Strich et al., 2021) attest to deterioration in domain experts’ capabilities to understand how such outputs were created and to validate them confidently, erosion that places organizations at high risk of not being able to respond to circumstances that are beyond the algorithmic decision-making’s capabilities. As Oliver et al. (2017) in particular have highlighted, inadequate responses to anomalous situations can lead to financial losses and legal issues.

In addition to steering for beneficial outcomes and finding mechanisms to remedy or preclude detrimental effects, knowledge-work organizations need to map out and consider the transformation path as they develop, implement, and fully deploy technologies that set in motion transformation of work roles and skill requirements. Reaping such benefits as
improved efficiency relative to solely human-based operations requires them to step onto a socio-technical journey that requires effort from experts in multiple domains and cooperation across profession boundaries. Therefore, it is no wonder that developing and implementing cognitive technologies is associated with managerial difficulties (Keding, 2020; Whittaker et al., 2018) such as delays in broad-based AI system development. Clearly, embarking on the process of weaving cognitive technologies into the socio-technical fabric of an organization is a complex endeavor. As the process progresses, various work practices and activities related to digital technologies emmesh and come to condition one another over time (Mousavi Baygi, Introna, & Hultin, 2021). Because of the temporally situated conditioning and other complexities entailed, one should approach the move to – and skills maintenance connected with – transformed work roles and skills in knowledge-intensive work as an ongoing effort. Attentiveness to conditions that can cultivate or stifle meaningful action along the way is critical for reaching the goals set by the organization for the transformation, be they instrumental, humanistic, or both.

Because developing and implementing cognitive technologies for use in knowledge-intensive work is a long-term process with complex dynamics and sets of consequences, organizations that embark on a transformative journey need to consider how to weave the cognitive technologies into their socio-technical fabric purposefully, to address the technology-sparked changes in practices, work roles, and skill requirements appropriately. Approaching the transformation’s management as a holistic endeavor can help practitioners and scholars make sense of how such conditions’ generative dynamics are best amplified and, on the other hand, how to prevent the establishment of disruptive dynamics that could precipitate developments likely to prove detrimental in the long term.

1.1 The objectives for the research

To enrich understanding of the complex dynamics that unfold as knowledge-work organizations introduce cognitive technology – including the beneficial and detrimental ramifications for practices, roles, and skills, researchers can explore the formation and transformation of the practices that contribute to development, implementation, and use of such technologies in knowledge-intensive work. The resulting understanding forms a vital foundation for understanding how individuals and organizations contribute to fostering beneficial dynamics and constraining disruptive ones, alongside how the new dynamics transform the various dimensions of knowledge-intensive work. Shedding light on this phenomenon is crucial for comprehending and managing the implications as cognitive technology (especially AI-based systems) gains momentum in corporate, governmental, and other organizations.

Most work on such matters has focused on debating the extent of replacing or complementing humans with cognitive technology and finding a balance between these two approaches – automation and augmentation, respectively (Asatiani, Penttinen, Rinta-Kahila, & Salovaara, 2019; Grønsund & Aanestad, 2020; Raisch & Krakowski, 2021). Systems utilizing AI have received the lion’s share of the attention because, being less transparent than rule-based cognitive technologies are, they generate less predictable errors (Jussupow et al., 2021). Accordingly, studies have begun to address issues such as the cognitive challenges of AI-based decision augmentation (Jussupow et al., 2021) and finding reliable ways of training and evaluating AI tools (Lebovitz, Levina, & Lifshitz-Assaf, 2021). In addition, they have pinpointed complete reliance on automation as a vexing matter, highlighting that
maintaining skills requires practice (Raisch & Krakowski, 2021) on account of the fact that “tacit and explicit knowledge mutually enhance each other towards increasing capacity to act” (Nonaka & von Krogh, 2009). The process whereby humans’ dynamic way of knowing transforms (Lebovitz et al., 2021) might even disintegrate if cognitive technologies’ immediate instrumental outputs are accorded greater weight than tacit aspects of experts’ knowledge processes and know-how (Feldman, 2004): decisions meant to enhance performance might backfire over time (Garud & Kumaraswamy, 2005) in organizations that have not fully addressed the dynamic complexity (Senge, 2006). Research demonstrates that augmenting humans’ work with AI is difficult to organize overall, and such failures are emerging already and indeed have proven to be commonplace (Raisch & Krakowski, 2021).

With so many issues tying in with the transforming dynamics and implications of cognitive technologies, academia has left numerous elements, at the level of organizations and individuals both, unaddressed. The dissertation project’s overarching objective was to address this gap by advancing and extending understanding of the shift in dynamics that begins to unfold as cognitive technology enters organizations’ use. The resulting insight should enable recognizing when beneficial vs. disruptive patterns are taking hold, the transformative effects on individuals and organizations, and the meaning of this transformation. The project’s research delved especially into the processes of automating and augmenting knowledge-intensive work, which have remained under-studied (Brynjolfsson & Mitchell, 2017; Grønsund & Aanestad, 2020). Drawing connections between knowledge gleaned from studying knowledge-intensive work’s changing processes and more thorough awareness of shifting socio-technical dynamics aids in fleshing out the picture of novel cognitive technologies’ implications at macro and micro level. For example, will automated systems replace human experts such as financial accountants, as has been predicted (Frey & Osborne, 2017), and what alternative paths may be available? With the three essays integral to the dissertation, I focused on addressing particular gaps in empirical work related to the changing nature of knowledge-intensive work.

The first essay examines AI system implementation’s influences on formal work practices and individuals’ action patterns – in other words, ostensive and performative aspects of routines. Through the shift in routines’ dynamics, the work roles of knowledge workers influenced (either directly or indirectly) by use of the AI system get transformed. To shed light on this phenomenon, I asked the following question:

RQ1: How does transition toward human–AI work affect work roles in knowledge-intensive work through shifts in routines’ dynamics?

Essay 1, focused on this question, addresses how those work roles changed at a company implementing and rolling out a cognitive technology (an AI-based system). As both the ostensive and the performative elements began to transform, this reconfiguration initiated transformation to the roles of the knowledge workers responsible for the related work process on ostensive and performative dimensions. This case study illuminated how routines’ dynamics may change as knowledge workers begin to adapt their patterns of action to accommodate use of an AI-based system and the new organizational guidelines related to it.

The second essay examines another case, of an organization where knowledge workers responsible for a specific work process had, through over-reliance on a rule-based cognitive system for handling it automatically, lost their skills in carrying out the related work tasks.
The skill erosion had occurred latently over time, and only withdrawal of the cognitive automation revealed the extent of these organization-members’ skill erosion. The essay dealt with two research questions. Firstly, it opened the complex dynamics of the phenomenon to consideration by examining the following issue:

RQ2: How does exploiting cognitive operations’ automation contribute to the erosion of knowledge workers’ skills?

Essay 2 presents a system-dynamics model created to illustrate and describe the various processes, mechanisms, and feedback loops that had contributed to skill erosion taking hold in the case organization. The second question addressed in essay 2 was this:

RQ3: How might such skill erosion affect organizations?

Since the skill erosion revealed had developed latently over an extended time, a situation arose wherein the organization no longer possessed the skills required for handling the work process and the related tasks it was responsible for performing on its clients’ behalf. The remedy required that the individuals whose skills had withered undergo intensive training, to relearn those skills. The essay underpins its discussion in the organization’s experience of having to devote considerable resources both to training its own knowledge workers such that they were above the required skill threshold again and to procuring services from external consultants so as to rebuild its capabilities for the relevant work process rapidly.

Finally, the third essay, returning to the empirical case examined in the first one, provides a broader look at the process of developing, implementing, and maintaining the use of an AI system. This essay’s focus is on outlining how a combination of practices and continuous actions invoked both generative and degenerative dynamics in the knowledge-intensive work. The essay answers the following question:

RQ4: Why do AI system development and deployment projects experience delays in knowledge-work organizations?

The essay highlights how, together, the temporal conditioning of humans’ practices and the actions of digital technologies dynamically shape the formation of an AI-based system and the transformation of practices. Examination of the data facilitated exploring ways in which delays to AI system implementation can arise when convergence fails – i.e., if the practices and actions cannot jointly cultivate conditions that favor correspondence. In addition to discussing conditions that can impede meaningful action along the (trans)formative path, the essay was intended to demonstrate a novel approach to the information-systems (IS) field and reflect on that approach.

1.2 Definitions of key concepts

In the dissertation project, I drew on a socio-technical perspective to strive for a balanced view of the instrumental and humanistic outcomes of technology (Sarker et al., 2019) and, thereby, account for the interconnected elements of social components (the humans and organizational arrangements) and technical ones (technology, tasks, and processes). Among the instrumental outcomes sought in such work are improved
performance and efficiency, and the humanistic outcomes comprise greater meaningfulness of the work and new skills.

**Knowledge-intensive work** is sets of tasks or work processes that require specialist knowledge, skills, and expertise, typically arrived at through formal education/training or extensive experience. This type of work usually involves the creation, manipulation, or dissemination of information or knowledge, and it often requires using, information systems, cognitive technologies, special techniques, etc. (Ditillo, 2004; Kogut & Zander, 1992). Some examples are financial services, legal services, software development, and data analysis. In these fields, **knowledge workers** rely heavily on their knowledge and expertise to perform their tasks effectively and efficiently, often in collaboration with other knowledge workers. A **knowledge-work organization**, then, focuses primarily on utilizing the skills and expertise of its employees to produce outputs that require cognitive effort. In addition to performing routine and repetitive tasks, knowledge-work organizations rely on employees' abilities to think critically, analyze information, and solve complex problems.

Machine learning (ML) applies models that build on algorithms, which, in turn, are pieces of code (instruction) that enable and specify rule-based and, hence, predictable calculations. A **machine-learning model** uses algorithms as a basis for learning, following the algorithms’ rules as it goes through training data to condition the model (Mitchell, 1997). However, what the model learns may not be entirely predictable, and one cannot always understand/explain the outputs. Therefore, training and fine-tuning of the model takes a large amount of time.

An **AI system** is an IS in which the ML model’s core task is to create algorithmic outputs. Users of an AI system interact with it through some user interface, and the system can be designed with embedded explanations of the algorithmically generated outputs, to improve the understandability of those outputs. An AI system may be relatively independent or be subordinate to / part of some other IS (e.g., it might enhance pre-existing features by providing suggestions that the human users can act upon at their discretion).

The concept of **human–AI work** refers to a collaborative work process in which the humans and AI system(s) work together to complete tasks, solve problems, and reach goals. This type of work involves AI tools, algorithms, and automation technologies all integrated with human capabilities, such as domain expertise and decision-making skills. In human–AI work, people and AI systems function in tandem to exploit each other’s strengths and compensate for each other’s weaknesses (Lyytinen et al., 2020; Rai et al., 2019). For example, AI systems can perform repetitive and mundane tasks quickly and accurately, while humans can supply context, judgment, and creativity to complex decision-making processes.

### 1.3 The structure of the dissertation

The dissertation has two main parts: Part I provides an integrative framing via an overview of the research objectives, key concepts, methods, results, and implications involved, and Part II presents the three essays that form the core of the original research contribution. Part I is structured such that the general introduction is followed by a presentation of the background in theory upon which the three essays build (in Chapter 2) and an outline of the methodology for the dissertation. The latter, presented in Chapter 3, goes through the
philosophical assumptions that underpin the research, describes the two empirical settings where data were collected, and then details both the data-collection processes and the systematic analysis. Against this backdrop, the next chapter provides a synthesizing discussion of the results from the three component studies (dealt with in the dissertation’s individual essays). Finally, with Chapter 5, I discuss the implications of the research conducted in the dissertation project, with regard to both theory and practice, before concluding the framing by examining the work’s limitations and, accordingly, opportunities for further research.

Part II is a compilation consisting of the three essays:

2. “The Vicious Circles of Skill Erosion: A Case Study of Cognitive Automation” (Rinta-Kahila, Penttinen, Salovaara, Soliman, & Ruissalo; accepted for publication)
3. “Fluid Socio-Technical (Trans)formation of an AI System” (Ruissalo, Penttinen, & Asatiani, published in 2022)
2. Theoretical background

This chapter provides an overview of the three bodies of literature that constitute the theoretical background for the dissertation. I begin with literature on organizations’ implementation of cognitive technologies, then outline prior work on the ramifications of such technologies for practices, work roles, and skills in knowledge-intensive work. Finally, I characterize scholarly attention to theoretical perspectives suitable for exploring and describing the transformative dynamics that begin taking shape as cognitive technology is implemented in knowledge-work organizations.

2.1 Organizational implementation of cognitive technologies

As advances in cognitive technologies – from advanced rule-based systems such as robotic process automation (RPA) to AI systems with ML models at their core – accelerate their permeation of knowledge-work organizations (Davenport & Ronanki, 2018), IS researchers are directing increasing attention to implementation of these systems, especially the use of learning-capable models (Faraj, Pachidi, & Sayegh, 2018; Rai et al., 2019; von Krogh, 2018) and the systems’ implications for everyday work in settings such as recruitment (van den Broek, Sergeeva, & Huysman, 2021), medical diagnosis (Jussupow et al., 2021; Lebovitz et al., 2021), and policing (Waardenburg, Huysman, & Sergeeva, 2022).

The newer technologies demand new considerations. While technologies such as RPA (see Lacity & Willcocks, 2016) and “expert systems” of various types require humans to set step-by-step rules for the systems, whereby the specification of execution steps or codification of explicit expert knowledge (Forsythe, 1993) renders the logic explainable and provides for specific, mostly expected outcomes, ML models act autonomously and proceed from historical data (Newell & Marabelli, 2015) to make predictions that may lack transparency. Their logic can be much more difficult to understand (Faraj et al., 2018; Jussupow et al., 2021) than that of rule-based cognitive technologies. Furthermore, AI systems’ algorithmic agency is increasing (Baird & Maruping, 2021). This too calls for revisiting the role of the human expert in the decision-making loop (Asatiani et al., 2019; Grønsund & Aanestad, 2020).

One key factor in the role dynamics is the set of purposes behind the organization’s use of cognitive technology. The concepts of automation and augmentation provides a useful starting point (Raisch & Krakowski, 2021). Scholars characterize an automation-based approach as focused on offloading repetitive tasks (which can be quite complex) to the technology; here, the cognitive technology can be regarded as substituting for human cognitive effort by taking on the work tasks (Krakowski, Luger, & Raisch, 2022). With augmentation, in contrast, cognitive technology functions to complement humans’ cognitive
efforts and decision-making by, for example, recommending possible conclusions/decisions for a given task and, moreover, providing seeds for human experts’ insight via information (Krakowski et al., 2022; Rai et al., 2019; von Krogh, 2018; Zuboff, 1988). While they can assist with some perspectives, AI systems are blind to others, in that they suffer from the “frame problem” (Salovaara, Lyytinen, & Penttinen, 2019): AI agents are unable to act competently in situations for which they lack predetermined rules. These situations demand augmentation by human experts, as Grønsund and Aanestad (2020) note. Recognizing such aspects of mutual complementarity opens the doors to human–AI work that factors in both parties’ weaknesses and strengths well. Cognitive technologies and humans can be brought together dynamically to function as a unit (Rai et al., 2019). Scholars pondering how to go about this refer to fluid use of cognitive technologies that entails dynamically transitioning between automation- and augmentation-oriented approaches (Lyytinen et al., 2020; Rai et al., 2019).

Such theoretical understanding aids in grappling with the need to balance the unintended consequences entailed by cognitive technologies’ implementation with the appealing proposition that makes these technologies so alluring for business managers. The lens of generative and degenerative dynamics (Senge, 2006; Mousavi Baygi et al., 2021) offers another tool for illuminating what begins to unfold in the socio-technical system as such technologies enter play. Another stream of work, looking beyond the implementations themselves, has examined these consequences and dynamics more closely.

### 2.2 Cognitive technologies’ implications for knowledge-intensive work

The second area of research supports considering the substitutive and complementary elements of the capabilities of cognitive technologies from another angle while also speaking to the contention of Rossi, Nandhakumar, and Mattila (2020) that we have very limited understanding of particular technologies’ dynamic shaping of routines and the fluidity in knowledge-intensive work. These factors warrant academic inquiry into the implications of cognitive technologies’ implementation and subsequent use with specific regard to work practices, roles, and skills in knowledge-work organizations.

As D’Adderio (2011) has pointed out, artifacts such as cognitive technologies are vital for both performing and transforming patterns of action (practices), where the technological artifacts help transfer routines across settings but at the same time contribute to their transformation. Identifying another temporal component, Grønsund and Aanestad (2020) noted that humans and the cognitive technology get configured and reconfigured in several ways over the course of the technology’s implementation and as its use in the organization evolves further. They also call attention to the finding that, if the technology is to meet the organization’s needs rather than merely take the place of human experts, each novel configuration must be complemented with readjustment to earlier roles and the articulation of expertise requirements.

From their study of technology-impelled adjustments to fingerprint technicians’ work roles, Davis and Hufnagel (2007) drew attention to work-practice changes that came bundled with the efficiency benefits of implementing a cognitive-automation system. These changes led to cognitive dissonance for some of the workers while being welcomed by others on account of concomitant improvements to their work position. Likewise, research examining AI that had been implemented in a banking context with the intention of hand-over of loan consultants’ tasks and responsibilities highlighted similar negative disruption impinging on the humans’
work identities, alongside alleviation of some pressures they were facing in their work (Mayer et al., 2020; Strich et al., 2021). These findings support the view that organizational change occurs through transformations in the entity’s arrangements – i.e., patterns of action and roles (Feldman & Pentland, 2003; Volkoff, Strong, & Elmes, 2007).

As several studies (e.g., Davis & Hufnagel, 2007; Grønsund & Aanestad, 2020) underline, the skills required for working in a specific prevailing socio-technical setting often need to be readjusted. A good starting point for articulating the first aspect of this matter, the meaning of “skills,” is the frequently employed division into declarative and procedural knowledge (Anderson, 1993), where the former encompasses the explicit facts and information expressly known (Kogut & Zander, 1992) while procedural knowledge, consisting of “accumulated practical skill or expertise that allows one to do something smoothly and efficiently” (von Hippel, 1988, p. 6), is implicit and rooted in our action (Nonaka & von Krogh, 2009; Schön, 1983).

Secondly, the readjustment happens through reskilling and upskilling efforts (Davenport & Kirby, 2016; McGuinness et al., 2019), aimed, respectively, at learning skills outside one’s current expertise and, usually with the goal of improving performance, expanding existing skills. These efforts often lead to developing skills in entirely foreign domains, such as IT use (Bravo, 2015), analytics (Zuboff, 1988), and management or social interaction (Agnew, Forrester, Hassard, & Procter, 1997). Furthermore, since the learning is intended to facilitate new kinds of interaction (e.g., for grappling with a socio-technical system where cognitive technology is in use), this change in interactions brings changes in humans’ capability of reflection, since contemplation often unfolds alongside interaction (Dittrich, Guérard, & Seidl, 2016). As Alvesson, Hardy, and Harley (2008) have noted, the reflection necessary in settings that require rapid action and in which time is short (such as knowledge-intensive activities) need not interfere with the activity at hand. It is important to highlight two distinct types of reflection: “reflection-in-action” is engaged in practice, embedded, and embodied, and “reflection-on-action” takes place prior to or after action and examines what has occurred or might happen (Yanow & Tsoukas, 2009).

An opposing phenomenon related to declarative and/or procedural knowledge is skill erosion, deterioration of the skills learned. Because skill requirements are likely to evolve in conjunction with cognitive technology’s adoption (see Grønsund & Aanestad, 2020), skill erosion and hindrances to acquisition of relevant knowledge may come hand in hand (Arnold & Sutton, 1998; Axelsen, 2014). Another factor connected with skill erosion is the crucial distinction between intended and unintended loss/weakening of skills – while many scholars and practitioners find the obsolescence of specific skills through new technologies’ rise unproblematic (Tushman & Rosenkopf, 1992), unintentional skill erosion that stems from extensive reliance on cognitive technology in settings such as auditing operations can bring detrimental effects (Arnold & Sutton, 1998; Dowling, Leech, & Moroney, 2008; Mascha & Smedley, 2007). Using the term “degeneration effect” to denote skills beginning to wither and gradually getting lost, Carr (2015) captures the fact that skill erosion is more likely in cognitive-technology settings that manifest mindlessness – that is, when the human expert is in “a state of reduced attention that tends to lead to mechanically employing cognitively and emotionally rigid, rule-based behaviors” (Fiol & O’Connor, 2003, p. 58), adhering strictly to set patterns of repetitive action (Thatcher, Wright, Sun, Zagenczyk, & Klein, 2018).
2.3 Cognitive technologies’ transformative dynamics

For researchers wishing to examine the complex dynamics that unfold with cognitive technologies’ deployment for knowledge-intensive work processes and the ensuing consequences, there is a rich spectrum of perspectives that can be applied. This dissertation’s three essays each draw on particular approaches that aid in unpacking the complexities involved in the phenomena under study.

2.3.1 The routine-dynamics perspective

The first of them is centered on routines, which Feldman and Pentland (2003) define as “repetitive, recognizable patterns of interdependent actions, carried out by multiple actors.” Rather than view these as stable entities (Nelson & Winter, 1982) or mistakenly regard them as rigid, mindless, or mundane (Cohen, 2005), scholars taking a routine-dynamics perspective apply a performative lens. This allows accounting for both the stability that is being continually re-enacted and the change as enactments evolve (D’Adderio, 2008) in the form of a recursive cycle of the two aspects (the ostensive and performative) that mutually constitute routines. In this conceptualization, the ostensive aspect is made up of enacted patterns alongside the rules and principles that guide the action patterns, while the performative aspect consists of what is actually done in specific performances. Approaching routines from this perspective affords examining them as repetitive, recognizable patterns of interdependent actions but also as practices with internal dynamics (Feldman & Pentland, 2003). While routines’ existence in organizations accentuates their temporal nature, routines are seldom perceived as temporal action patterns or involving potential for change, though they do not seem to be static or fixed things either – routines exist through a process of production and reproduction that functions via ongoing efforts wrought by people and things in a socio-technical system (Feldman, Pentland, D’Adderio, & Lazaric, 2016).

With a second distinction, scholars can identify changes in routines as either adaptive or generative (Parmigiani & Howard-Grenville, 2011; Pentland & Feldman, 2005; Pentland et al., 2012). Whereas the notion of adaptive change represents adapting to exogenous changes by creating variations from a position external to the routines (Nelson & Winter, 1982; Pentland & Feldman, 2008), that of generative change implies creative endogenous local enactments by emphasizing internal dynamics and performances of routines that bring about variations and allow change to take hold (Bucher & Langley, 2016; Pentland et al., 2012). These two types of change can be perceived in the dynamic interaction among the ostensive aspect, the performative, and a third aspect: the material (Pentland & Feldman, 2005; Volkoff et al., 2007). When routines become embedded in technology, they gain a material aspect that begins to condition the ostensive and performative aspects of routines by interacting with them (Volkoff et al., 2007). Among this emerging aspect’s components are routine enactment that includes technological artifacts and the way in which interactions between actors and the components of routines happen in practice (Pentland et al., 2012). Thus, in addition to dynamics of routines, technological artifacts are essential to the execution and change of routines (D’Adderio, 2011) as they both assist in transferring routines and contribute to their continuous transformation and evolution (D’Adderio, 2014). Accordingly, a routine-dynamics perspective affords addressing both the shift in routine enactments of actants and the technology. Its lens holds value for looking at socio-technical transformation in knowledge-work organizations.
2.3.2 A systems perspective and the system-dynamics lens

Work in general systems theory and cybernetics laid the foundations for the systems perspective (Ashby, 1957; Boulding, 1956; von Bertalanffy, 1968), which builds on the notion that systems and their elements interact in a dynamic manner (Boulding, 1956; Burton-Jones, McLean, & Monod, 2015). With this perspective, scholars extended their gaze beyond unidirectional views such as those typical of process-oriented research. A systems perspective assists in considering information-systems-use-related phenomena in organizations by expanding our understanding of dynamic, complex management-linked phenomena wherein an information system exhibits emergent effects, per Senge (2006). With this lens, he points out that a given managerial action may differ substantially in its effects on the basis of the timeframe and that its consequences may vary between parts of the system.

While system-dynamics methodology (as applied in Senge’s work) was initially used primarily for creating mathematical models and simulations (Forrester, 1961), IS and management studies (Baker & Singh, 2019; Fang, Lim, Qian, & Feng, 2018) have since employed it for conceptual modeling in interpretive research (Baker & Singh, 2019). When modeled from a system-dynamics angle, a socio-technical system is depicted as composed of causal loops (Senge, 2006); the model diagrams the dynamic processes via feedback loops among the system’s elements (Fang et al., 2018). Effects developing between these elements are categorized as reinforcing and balancing, where the system’s balancing loops lead to self-limiting effects and the reinforcing loops produce self-sustaining ones (Senge, 2006). To provide a foundation for modeling system dynamics, theoreticians have developed several system archetypes (Kim, 1992; Senge, 2006) around which more comprehensive models can coalesce.

2.3.3 Flow-oriented approaches

For understanding the continuing evolution of cognitive technologies’ interplay with new dynamics in organizations, the novel theory of socio-technical transformation proposed by Mousavi Baygi et al. (2021) offers an alternative way of unpacking and depicting the complex dynamics. This theory focuses on how flows of people and digital technologies temporally condition the ways in which the flows are continuously becoming. Whereas an actor-centric perspective casts the originators of formation and transformation as self-contained entities involved in the ongoing process, those taking a flow-oriented approach see the socio-technical (trans)formation’s origin as lying in the becoming and conditioning of historical and new lines of action that create new possibilities for action along the flows as they enter or fall out of correspondence with one another.

Under this approach, flow is one of two central concepts that merit attention. Flow is a quality that forms as previous lines of action get absorbed and continuously woven into new paths (Chia, 2002). In this conceptualization, entities are always in the making as the flows of action sweep them away and simultaneously animate them in a continuous open-ended process. For scholars taking such a perspective, the flowing lines of action cannot be reduced to sequences of chronological instances, acts, events, or episodes. Therefore, the flow-oriented approach marks an important shift in the notion of time, from chronos to kairos – from a chronological order to kairological time that goes beyond any single timeline. As attention shifts to kairotic timing and the temporal qualities of flows of action (rhythms, timeliness, and directionalities, each entailing specific (trans)formative dynamics), the timing
brings timely moments into the spotlight. Such a moment is a confluence of various flowing lines of action along a shared path, each with its inherent temporal qualities. These flowing action lines and their confluences can be illustrated as a kairotic meshwork (Ingold, 2015).

The second core concept is correspondence, developed by Ingold (2011, 2015) to address what occurs as multiple flowing lines of action get woven together such that specific (trans)formative dynamics of creation, sensing, and actualization can emerge. As Mousavi Baygi et al. (2021) noted, development of (trans)formative dynamics along socio-technical flows requires that the flowing lines of action reach correspondence through three modalities – namely, timing, attentionality, and undergoing. These modalities entail a moment of kairotic timing, an attentional orientation, and an experience of undergoing. Timing enables creating conditions for new possibilities of action along flows, attentionality forms room for sensing possibilities of action, and undergoing affords actualizing them along a (trans)formative path. As the dynamics of creation, sensing, and actualization enter alignment, the flowing lines of action can become co-responsively interwoven. This convergence forms and transforms the temporal qualities and trajectories of the flowing lines of action that compose and shape the (trans)formative path of becoming.

A flow-oriented perspective thus provides tools for examining how cognitive-technology development, implementation, and use informs specific dynamics along the socio-technical (trans)formative path of becoming as various corresponding flows of action condition and come to be conditioned by new practices and algorithmic action. The resulting standpoint, in turn, allows us to explain how the entities involved are subject to conditioning and, thereby, how temporal qualities such as directionalities of action shift as the path unfolds. Therefore, a flow-oriented approach facilitates accounting for the ongoing nature of (trans)formation and its vibrancy as several flowing lines with their temporal elements reach convergence.

### 2.4 Situating the literature review

My survey of the literature demonstrates that there is much ground to be covered for extending knowledge of socio-technical dynamics’ transformation amid cognitive-technology development and deployment and of that process’s implications for knowledge-intensive work. Since it highlighted multiple unaddressed issues at the levels of both organizations and individuals, with the dissertation project I sought a holistic way of illuminating these pattern shifts that begin to unfold in organizations as a new cognitive technology enters use. Delving more deeply into the processes of automating and augmenting knowledge-intensive work should enable scholarship to address the dearth of attention to the intricate level-specific threads in the transformation tapestry (Brynjolfsson & Mitchell, 2017; Grønsund & Aanestad, 2020). Considering what can be learned from studying knowledge-intensive work’s changing processes in combination with awareness of the shifting socio-technical dynamics affords enriching our knowledge of the novel technologies’ implications for individuals. This, in turn, facilitates addressing under-studied issues of the breadth and depth of cognitive technologies’ impact on professions – especially those expected to be significantly affected by the socio-technical change implied, such as financial accounting (Frey & Osborne, 2017) – and on organizations too. Also, it creates an opportunity to clarify implications and critically probe for specific predicted effects of this transformation. Table 1 lists the main issue pinpointed by each body of literature that, with the project, I aimed to address in pursuit of more comprehensive and nuanced understanding of socio-technical transformation dynamics.
Table 1. Issues identified in relation to cognitive technology’s development, deployment, and use in knowledge-intensive work

<table>
<thead>
<tr>
<th>Topic of literature</th>
<th>Issue identified</th>
</tr>
</thead>
<tbody>
<tr>
<td>The learning ability of ML-enabled systems</td>
<td>Lack of the explainability and output transparency required for the human expert to remain in the loop</td>
</tr>
<tr>
<td>Automation- and augmentation-oriented approaches to cognitive technology</td>
<td>Emphasis on individual agents rather than the mutual interactions that form a better lens for examining transformation of work roles</td>
</tr>
<tr>
<td>Application of cognitive technologies in knowledge-intensive work</td>
<td>The continuing need for detail-level understanding of the process of routines’ and human–AI configurations’ dynamic shaping</td>
</tr>
<tr>
<td>Routine-dynamics studies</td>
<td>Lack of knowledge of technological artifacts’ effects whereby dynamics of routines lead to degenerative and/or generative outcomes</td>
</tr>
<tr>
<td>System dynamics</td>
<td>Poor knowledge of the mechanisms at socio-technical system level that alter the dynamics of knowledge-intensive work</td>
</tr>
<tr>
<td>A flow-oriented approach</td>
<td>The dearth of knowledge of performative becoming that would enable explaining the dynamics of socio-technical transformation without an appeal to self-contained agents</td>
</tr>
</tbody>
</table>
3. Methodology

3.1 Assumptions

Any theoretical perspective necessitates methods consistent with its underlying ontological and epistemological assumptions. Social science and the IS field offer three main alternatives for the onto-epistemological paradigm (i.e., the underlying belief system with its particular ontological, epistemological, and methodological assumptions) (Guba & Lincoln, 1994). The three paradigms under which most information-systems research falls are positivism, interpretivism, and critical realism (Mingers, 2011; Orlikowski & Baroudi, 1991).

Positivism usually assumes a realist ontology wherein social reality is regarded to exist independently of our knowledge and to be measurable and explainable through objective methods (Guba & Lincoln, 1994; Orlikowski & Baroudi, 1991). Interpretivism takes an opposing view by presuming that reality is socially constructed and given meaning by interaction between people, where knowledge is created through intersubjective interpretation (Walsham, 1995). Expressing criticism of both positivist and interpretivist approaches, critical realism asserts a claim that positivism and interpretivism suffer from the epistemic fallacy – i.e., from conflation whereby ontological issues can be reduced to epistemological ones (Mingers, Mutch, & Willcocks, 2013). Critical realism assumes realist ontology and epistemological relativism: reality is independent of our conception of it (Bhaskar, 1975), and knowledge is created intersubjectively.

Since the research in which I have been engaged is aimed at qualitatively interpreting human perceptions and how they interact with one another and technology amidst the ongoing socio-technical transformation, the onto-epistemological stance that I take is best described as following the paradigm of interpretivism. From this standpoint, developing interpretations and furnishing a properly described context are essential to the researcher’s interpretations, wherein the reality is interpreted through the research participants’ experiences and views of the phenomenon in question (Myers, 1997; Orlikowski & Baroudi, 1991).

3.2 Empirical settings

The research behind this dissertation applied a qualitative design, and preparation of the three essays drew from two separate sets of rich empirical data. The arguments in essays 1 and 3 build on data from a qualitative longitudinal study producing data through June 2023, while the qualitative data presented in the other essay come from a case study in a research project completed earlier. Detailed description of both empirical settings is presented below.
3.2.1 Longitudinal research

Preparation and planning for the research project began in September 2019. In December of that year, discussions with a potential case company in the financial-management services sector produced an agreement on a longitudinal study designed to focus on exploring the unfolding effects of cognitive technologies on the work practices, roles, and skills of knowledge workers – the organization’s accountants. The company, which had started to develop an AI system in June 2019, planned to deploy that system for gradual rollout in its knowledge workers’ activities. Early piloting began in November, and only a couple of accountants had participated in piloting by that point, so this company offered an ideal setting for starting to track changes from the pre-implementation phase onward and, in the process, capturing the accountants’ perceptions of the AI system, alongside the RPA that had been in use for some time already in a few minor financial-accounting tasks, and their attitudes toward it.

The study focused on a large Finnish company specializing in financial-accounting and payroll-administration services. Along with local offices in several parts of Finland, it had set up a shared-services center (SSC) to centralize certain types of accounting work in a single location such that dedicated teams would conduct specified financial-accounting processes for accounts payable, accounts receivable, and general-ledger accounting. Furthermore, in conjunction with a larger strategic initiative, the same year (2019) saw the case company create an AI innovation unit. It was the latter unit that began developing algorithms for an ML-model-based AI system with the goal of deployment to automate and augment performance of financial-accounting work tasks. The unit set out to utilize the historically accumulated purchase-invoice data in training of the AI system’s ML model. At the same time, handling of the financial-accounting process was restructured. An accountant had been responsible for the whole process before, but the process was now split such that accounts-payable and accounts-receivable work would belong to separate sets of accountants. Senior accountants, who usually possess more experience and expertise, would focus purely on general-ledger work, which usually features tasks with greater complexity.

I focused on the case company’s accounting process because the AI system had been designed, developed, and implemented for the purpose of generating posting predictions for invoice accounts more efficiently with the goal of letting the human experts’ time be directed to more productive tasks. Previously, accountants carried out the tasks of making correct postings by relying on the purchase invoices’ information and checking/validating the correctness of each account posting and value-added tax (VAT) value from the purchase invoice. For these work tasks, the accountants had been conducting high-volume processing of invoices by means of manual postings in the accounting-information system (automatic rule-based postings were set up, manually, for only invoices with entirely unvarying bookkeeping-account and VAT values).

Since the accounts-payable process therefore involves large quantities of invoices, with the postings for each being time-consuming, the AI development unit chose AI-generated account postings as the highest-priority use case, per its criteria. The development goal was for the ML model’s predictions for the fields for account postings and VAT values to reduce the involvement of human experts in the invoice-handling task, the most laborious part of the accounts-payable process. The system was designed such that a widget in the accounting-information system lists those of the AI-generated predictions that are below a specified confidence threshold, for the accountant to check, then correct or validate as
necessary. The developers consulted the accountants for information on the processes involved but not on this or other design decisions. One of those decisions was to leave it to each accounts-payable accountant’s discretion whether to activate the AI system for any particular client, by relying on the recommendation given by the AI system with regard to its expected accuracy. The slow rate of discretionary application later prompted a change in approach – the SSC director and other managers started jointly selecting client companies for which the AI system seemed suitable, and activations were done in large batches. However, the system still could be toggled for specific suppliers to each client company. On the basis of how well the AI system performs at the level of the client in question, the accountant can decide whether the system should be active or not for a given supplier, and in some cases it can even be deactivated for specific client companies.

In parallel with the AI system’s wider deployment, the case company is currently engaged in a process change aimed at moving a specific subprocess from general-ledger accountants’ responsibility to accounts-payable accountants’ so that the general-ledger ones end up with more time to handle such complex value-adding work as offering clients financial-analysis services.

### 3.2.2 Case-study work on skill erosion

With the next study, the initial aim was to explore how RPA could enhance financial-accounting work and what a case company’s knowledge workers thought about this novel technology. I contacted an international financial-accounting firm that was planning to implement RPA in its work processes and arranged to conduct interviews with the accountants who would be using that cognitively oriented automation: the SSC’s accountants and managers who delivered outsourced financial-accounting services to a large client base that represented various industries.

During the first interview, an unexpected pattern began to emerge, however. The accountant began describing how the company, specializing in the development of digital business solutions and financial processes, had discontinued its use of a sophisticated rule-based system for cognitive automation. As the interview delved into this situation’s specifics, the answers began revealing that the informant no longer had the skills necessary for some of the financial-accounting activities that had been handled automatically for several years (for fixed-asset management, FAM). Other accountants in the initial interviews at this Northern-Europe-based company described the same situation: they could no longer perform FAM tasks. After seven years of using cognitive technology designed explicitly to automate those tasks, the case company’s withdrawal of the system to simplify its IT architecture revealed that the accountants had forgotten how to carry out manual fixed-asset accounting.

In consequence, the organization embarked on an arduous process of learning-by-doing and forced employees to attend training sessions to regain lost skills. Furthermore, so that it could fulfill its responsibility for supplying its clients with FAM services, the company had to purchase consulting services from the provider of the cognitive-automation system.

### 3.3 The collection of data

Having described the settings for both the longitudinal study and the case study of skill erosion, I now turn to the data-collection processes followed.
3.3.1 The data in the longitudinal study

Access to the case company gave me an opportunity to start forming thick description of the socio-technical change through interviews with the accountants, supplemented by interviews with other experts and managers who could provide essential information on the transformation in progress.

The longitudinal study started in January 2020, when I carried out the first round of interviews in aims of forming a general sense of the accountants’ jobs and work content while also gauging their pre-implementation perceptions of the automation-based technologies (either the AI system or the RPA). The second-round interviews took place in the following September–October, when both the AI-based system and RPA had entered limited use. Round 2, therefore, focused on how the accountants’ perceptions and their attitudes to the system in question had evolved, whether the content of their work had changed, and how (if at all) their skill or competence requirements had changed during the implementation phase. I carried out a third set of interviews in May 2021, when the organization had very recently moved into its post-implementation phase, with the fourth round following in November to December. While both rounds were similar in focal topics to the second round, the accountants had since gained much more experience in using the automatic tools, and their perceptions of potential beneficial and detrimental effects of the AI system on their work practices had evolved.

The fifth interview round, arranged for May–June 2022, likewise had a similar agenda, but then it emerged that a significant process change would begin in September 2022, with the transition scheduled to continue into the first half of 2023. The piloting of this process change, connected with a recently commenced larger project for digital transformation, created an opportunity to gather several accountants’ perceptions of this upcoming change from very early on. With interviews in December 2022 – January 2023, I sought to capture the accountants’ perceptions and attitudes related to both the AI system in place and, additionally, the ongoing process transition and how the accountants had seen and experienced it affecting their work. Furthermore, I found out that the organization had paid more attention to developing training in the AI system, which led me to ask some of the informants about the background to this shift in attention.

Throughout the longitudinal study, semi-structured interviews with the accountants served as my primary source of data. The informants in the earliest stages were 12 accountants who would be using the AI system under development in their work and four accountants whose activities relied on those 12 accountants’ work outputs. As anticipated, personnel changes were highly likely at this time, so I strove for a sufficiently large sample that enough of the original participants would remain at the organization. Turnover did necessitate replacing a considerable proportion of the original set with other accountants, but some of the original participants nonetheless remain. In addition, including accountants who had not taken part in earlier phases of the AI implementation afforded insight as to how people representing multiple backgrounds understand and approach the use of the AI system.

When circumstances related to the pandemic made it impossible to meet with the informants in person, I conducted the interviews via Microsoft Teams. In addition to accountants, I have interviewed their team leaders, automation-development projects’ experts, and managers of the units involved, to enable forming a comprehensive picture of the socio-technical transformation. Table 1 lists all 28 accountants and six automation-
developers, team leaders, or managers included. The project has involved 96 interviews in total, thus far.

As it stands, the project is still in progress, with 11 accountants currently participating in the study. Eight are members of a team that is using AI for daily work, and three of them are on a team that is affected by the AI system’s outputs and uses RPA in specific work tasks. I plan to conduct the final round of interviews before the end of summer 2023, with emphasis on questions related to current perceptions and understandings of the AI system, the process change (likely to be largely complete), and the training program for the AI system’s main users. This round should mark the completion of a 41-month longitudinal study that has provided a rare opportunity for research systematically following the gradual change in the work practices, work roles, and skills of knowledge workers that arises in conjunction with AI’s, RPA’s, and work-process changes’ influence on their work.
## Table 2. Informants' background (1/4)

<p>| Interviewee (pseudonym) | Interview round number | Interview duration (minutes) | Age | Team | Work title          | Years with the company | Current areas of responsibility (total financial accounting experience in years) | Education                                      | Vocational Qualification in Business and Administration |
|-------------------------|------------------------|-----------------------------|-----|------|---------------------|------------------------|-----------------------------------------------------------------|---------------------------------------------|
| Adam                    | #1                     | 64                          | 22  | Team | 2                  | 0.5                    | Mainly AP and AR processes (0.5 years)                           | Vocational Qualification in Business and Administration |
|                         | #2                     | 29                          |     |      | Accounts payable and receivable | 1.75                   | GL accounting and reporting, financial statements (0.5 years)    | Bachelor of Business Administration |
|                         | #3                     | 58                          |     |      | Accounting specialist  | 2.5                    | GL accounting and reporting, financial statements (0.5 years)    | Bachelor of Business Administration |
|                         | #4                     | 45                          |     |      | Senior accountant     | 3.5                    | GL accounting and reporting, financial statements (0.5 years)    | Bachelor of Business Administration |
|                         | #5                     | 56                          |     |      | Accounting specialist  | 2.75                   | Management of finance activities, induction of new employees, and maintenance and development of finance-related skills | Bachelor of Business Administration |
|                         | #6                     |                             |     |      | Senior accountant     | 3.25                   | Management of finance activities, induction of new employees, and maintenance and development of finance-related skills | Bachelor of Business Administration |
| Amy                     | #1                     | 63                          | 37  | Team | 2                  | 0.5                    | Mainly AP and AR processes (0.5 years)                           | Vocational Qualification in Business and Administration |
|                         | #2                     | 29                          |     |      | Accounts payable and receivable | 1.75                   | GL accounting and reporting, financial statements (0.5 years)    | Bachelor of Business Administration |
|                         | #3                     | 53                          |     |      | Accounting specialist  | 2.5                    | GL accounting and reporting, financial statements (0.5 years)    | Bachelor of Business Administration |
|                         | #4                     | 56                          |     |      | Senior accountant     | 3.5                    | GL accounting and reporting, financial statements (0.5 years)    | Bachelor of Business Administration |
|                         | #5                     |                             |     |      | Accounting specialist  | 2.75                   | Management of finance activities, induction of new employees, and maintenance and development of finance-related skills | Bachelor of Business Administration |
|                         | #6                     |                             |     |      | Senior accountant     | 3.25                   | Management of finance activities, induction of new employees, and maintenance and development of finance-related skills | Bachelor of Business Administration |
| Beth                    | #1                     | 53                          | 34  | Team | 2                  | 0.5                    | Mainly AP and AR processes (0.5 years)                           | Vocational Qualification in Business and Administration |
|                         | #2                     | 56                          |     |      | Accounts payable and receivable | 1.75                   | GL accounting and reporting, financial statements (0.5 years)    | Bachelor of Business Administration |
|                         | #3                     | 43                          |     |      | Accounting specialist  | 2.5                    | GL accounting and reporting, financial statements (0.5 years)    | Bachelor of Business Administration |
|                         | #4                     |                             |     |      | Senior accountant     | 3.5                    | GL accounting and reporting, financial statements (0.5 years)    | Bachelor of Business Administration |
|                         | #5                     |                             |     |      | Accounting specialist  | 2.75                   | Management of finance activities, induction of new employees, and maintenance and development of finance-related skills | Bachelor of Business Administration |
|                         | #6                     |                             |     |      | Senior accountant     | 3.25                   | Management of finance activities, induction of new employees, and maintenance and development of finance-related skills | Bachelor of Business Administration |
| Bob                     | #1                     | 67                          | 31  | Team | 2                  | 1                      | Management of the team's activities, induction of new employees, and maintenance and development of team-related skills | Bachelor of Business Administration |
|                         | #2                     | 25                          |     |      | Accounts payable and receivable | 1.75                   | GL accounting and reporting, financial statements (0.5 years)    | Bachelor of Business Administration |
|                         | #3                     | 56                          |     |      | Accounting specialist  | 2.5                    | GL accounting and reporting, financial statements (0.5 years)    | Bachelor of Business Administration |
|                         | #4                     | 43                          |     |      | Senior accountant     | 3.5                    | GL accounting and reporting, financial statements (0.5 years)    | Bachelor of Business Administration |
|                         | #5                     |                             |     |      | Accounting specialist  | 2.75                   | Management of the team's activities, induction of new employees, and maintenance and development of team-related skills | Bachelor of Business Administration |
|                         | #6                     |                             |     |      | Senior accountant     | 3.25                   | Management of the team's activities, induction of new employees, and maintenance and development of team-related skills | Bachelor of Business Administration |
| Caroline                | #1                     | 53                          | 34  | Team | 2                  | 0.5                    | Mainly AP and AR processes (0.5 years)                           | Vocational Qualification in Business and Administration |
|                         | #2                     | 56                          |     |      | Accounts payable and receivable | 1.75                   | GL accounting and reporting, financial statements (0.5 years)    | Bachelor of Business Administration |
|                         | #3                     | 43                          |     |      | Accounting specialist  | 2.5                    | GL accounting and reporting, financial statements (0.5 years)    | Bachelor of Business Administration |
|                         | #4                     |                             |     |      | Senior accountant     | 3.5                    | GL accounting and reporting, financial statements (0.5 years)    | Bachelor of Business Administration |
|                         | #5                     |                             |     |      | Accounting specialist  | 2.75                   | Management of the team's activities, induction of new employees, and maintenance and development of team-related skills | Bachelor of Business Administration |
|                         | #6                     |                             |     |      | Senior accountant     | 3.25                   | Management of the team's activities, induction of new employees, and maintenance and development of team-related skills | Bachelor of Business Administration |
| Charlie                 | #1                     | 59                          | 31  | Team | 2                  | 1                      | Management of the team's activities, induction of new employees, and maintenance and development of team-related skills | Bachelor of Business Administration |
|                         | #2                     | 60                          |     |      | Accounts payable and receivable | 1.75                   | GL accounting and reporting, financial statements (0.5 years)    | Bachelor of Business Administration |
|                         | #3                     |                             |     |      | Accounting specialist  | 2.5                    | GL accounting and reporting, financial statements (0.5 years)    | Bachelor of Business Administration |
|                         | #4                     |                             |     |      | Senior accountant     | 3.5                    | GL accounting and reporting, financial statements (0.5 years)    | Bachelor of Business Administration |
|                         | #5                     |                             |     |      | Accounting specialist  | 2.75                   | Management of the team's activities, induction of new employees, and maintenance and development of team-related skills | Bachelor of Business Administration |
|                         | #6                     |                             |     |      | Senior accountant     | 3.25                   | Management of the team's activities, induction of new employees, and maintenance and development of team-related skills | Bachelor of Business Administration |</p>
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<tr>
<th>Interviewee (pseudonym)</th>
<th>Interview round number</th>
<th>Interview duration (minutes)</th>
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<th>Current areas of responsibility (total financial accounting experience in years)</th>
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*Columns: Interviewee (pseudonym), Interview round number, Interview duration (minutes), Age, Team, Work title, Years with the company, Current areas of responsibility (total financial accounting experience in years), Education, Vocational/Qualification in Business and Administration.*
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<tr>
<td>#6</td>
<td>*</td>
<td>*</td>
<td>*</td>
<td></td>
<td>*</td>
<td>*</td>
<td>*</td>
<td>*</td>
</tr>
</tbody>
</table>
3.3.2 Material for the case study of skill erosion

The skill-erosion case study involved, in total, 25 semi-structured interviews. Along with the 16 participants’ contributions, the study benefited from secondary data available online, collected to complement insight from the primary data. All told, the study comprised four data-collection components. Table 2, below, summarizes the process of the data collection.

Table 3. Inquiry elements and informants

<table>
<thead>
<tr>
<th>Element of inquiry</th>
<th>Organization</th>
<th>Interviewee</th>
<th>Role</th>
<th>Tenure at AccComp</th>
<th>Month of interview</th>
<th>Interview length</th>
</tr>
</thead>
<tbody>
<tr>
<td>1: Identifying the research problem and obtaining a general orientation to the organizational context</td>
<td>AccComp</td>
<td>Sue</td>
<td>FAM accountant</td>
<td>15 years</td>
<td>Nov. 2016</td>
<td>75 min.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Amy</td>
<td>FAM accountant</td>
<td>8 years</td>
<td>Nov. 2016</td>
<td>87 min.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Mary</td>
<td>Accountant (with some FAM duties)</td>
<td>5 years</td>
<td>Nov. 2016</td>
<td>82 min.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Donna</td>
<td>Accountant (with some FAM duties)</td>
<td>1 year</td>
<td>Nov. 2016</td>
<td>67 min.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Betty</td>
<td>Accountant (with some FAM duties)</td>
<td>2 years</td>
<td>Nov. 2016</td>
<td>75 min.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Susan</td>
<td>Accountant</td>
<td>4.5 years</td>
<td>Nov. 2016</td>
<td>72 min.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Patricia</td>
<td>Accountant</td>
<td>15 years</td>
<td>Nov. 2016</td>
<td>62 min.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Jennifer</td>
<td>Accountant</td>
<td>1 year</td>
<td>Nov. 2016</td>
<td>68 min.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Linda</td>
<td>Accountant</td>
<td>1 year</td>
<td>Nov. 2016</td>
<td>69 min.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>John</td>
<td>Team leader and FAM accountant</td>
<td>9 years</td>
<td>Nov. 2016</td>
<td>70 min.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Carol</td>
<td>Head of the SSC</td>
<td>3 years</td>
<td>Nov. 2016</td>
<td>56 min.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Sara</td>
<td>Manager</td>
<td>4.5 years</td>
<td>Nov. 2016</td>
<td>85 min.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Roger</td>
<td>Manager</td>
<td>4.5 years</td>
<td>Nov. 2016</td>
<td>55 min.</td>
</tr>
<tr>
<td>2: Gaining contextual understanding of the environment, task, and automation technology from the angle of skill erosion</td>
<td>FAMComp</td>
<td>James</td>
<td>Sales manager</td>
<td>N/A</td>
<td>Mar. 2017</td>
<td>30 min.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Mark</td>
<td>CEO/owner</td>
<td>N/A</td>
<td>Mar. 2017</td>
<td>25 min.</td>
</tr>
<tr>
<td></td>
<td>National Association of Accounting Firms</td>
<td>Daniel</td>
<td>Director of Member Services</td>
<td>N/A</td>
<td>Apr. 2020</td>
<td>32 min.</td>
</tr>
<tr>
<td>3: Focusing on how skill erosion occurred in the interaction of the task, technology, and participants within the organizational context</td>
<td>AccComp</td>
<td>Sue</td>
<td>Accountant</td>
<td>15 years</td>
<td>Mar. 2017</td>
<td>55 min.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Amy</td>
<td>Accountant</td>
<td>8 years</td>
<td>Mar. 2017</td>
<td>51 min.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>John</td>
<td>Team leader</td>
<td>9 years</td>
<td>Apr. 2017</td>
<td>48 min.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Carol</td>
<td>Head of the SSC</td>
<td>3 years</td>
<td>Jun. 2017</td>
<td>46 min.</td>
</tr>
<tr>
<td>4: Fine-granularity understanding and validation of conclusions</td>
<td>AccComp</td>
<td>John</td>
<td>Accounting manager</td>
<td>9 years</td>
<td>Apr. 2020</td>
<td>76 min.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>John</td>
<td>Accounting manager</td>
<td>9 years</td>
<td>May 2020</td>
<td>61 min.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Mary</td>
<td>Accountant</td>
<td>5 years</td>
<td>Aug. 2020</td>
<td>55 min.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Amy</td>
<td>Accountant</td>
<td>8 years</td>
<td>Aug. 2020</td>
<td>26 min.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Sue</td>
<td>Accountant</td>
<td>15 years</td>
<td>Sept. 2020</td>
<td>62 min.</td>
</tr>
<tr>
<td>Totals:</td>
<td></td>
<td>16 informants</td>
<td></td>
<td>25 interviews</td>
<td></td>
<td>1,490 min.</td>
</tr>
</tbody>
</table>
The first inquiry took place in November 2016 when I conducted initial interviews with 13 informants at the case company. For a systematic process, I had prepared a semi-structured interview protocol to guide the interview procedure, in which another researcher participated for three of the interviews. This protocol focused on the informants’ perceptions of the cognitive technology and its potential implications for maintaining one’s skills. When interviews with three experienced accountants revealed the circumstances related to discontinuation of the sophisticated rule-based automation of FAM tasks, the study’s focus narrowed to the latent skill erosion that recently had become apparent in the organization. For the second round of inquiry, adjusted in light of the phenomenon uncovered, two fellow researchers engaged with the cognitive-automation system’s provider to understand the system’s workings and prepare for in-depth study. This involved examining documents and videos that present how the system works and interviewing company personnel. In addition, they interviewed the director of member services for Finland’s National Association of Accounting Firms, for solid understanding of what FAM skills accountants should have.

Because the research team needed more thorough understanding of how skill erosion had taken root, a third round of inquiry was conducted, with informants who had been affected by the cognitive-automation system’s discontinuance. This time, specifically chosen informants were asked about organizational policies and practices related to the system’s use, how the accountants’ perceptions of the automated operations and their work tasks had evolved over time, the situation before the automation was implemented (for background information), issues that arose during its use, and their post-discontinuance experiences.

The final inquiry element was designed for validation of our findings after rigorous analysis of the data collected. That inquiry made it possible to reach deeper understanding of the processes of skill erosion and of relearning the lost skills, thereby increasing confidence in the findings’ validity.

3.4 Data analysis

With the data-collection processes of both empirical cases explained, I can move on to describing the processes of data analysis. Beginning with the processes behind essay 1 and essay 3 (both involving the longitudinal data set), I go through each of the two data-analysis processes separately.

3.4.1 Analysis in the longitudinal study

The main goal behind the preparation of Essay 1 was to identify what had transpired in the socio-technical system through the pre-, peri-, and post-implementation phases of the AI system’s development and deployment process with regard to transformation of the knowledge workers’ routines and roles.

Since I had conducted every interview myself, kept field notes, and received materials from the company, I had established a comprehensive background for situating the interview content and was acutely aware of contextual nuances. Transcription of all the interviews allowed me to return to specific informant responses easily. Proceeding from these materials, I carried out preliminary analysis for the study. Beginning with the pre-implementation situation, I set out to identify the main routines (formal work processes, informal patterns of working, etc.). Already at this point, I attempted to capture the ostensive and performative aspects as accurately as possible.
In the second stage of analysis, I began identifying in a similar manner what had changed as the implementation and post-implementation phases progressed and how the accountants interacted with the system then – for example, how they used it, whether its use posed some issues for them, and whether they had ceased any of their pre-implementation activities. The analysis also encompassed the manner of designing and developing the ML model’s algorithms and which task performances the AI system had automated or augmented.

Thirdly, I examined the three phases to identify activities and responsibilities distinctive of each phase and also compared between the implementation and the post-implementation phase to assess how the accountants’ patterns of using the AI-based system had changed. Furthermore, I analyzed the sensemaking process of the data scientist interviewed, who had been involved in the AI system’s development from the beginning, while also considering what that informant had revealed about other innovation team members’ activities and sensemaking.

This analysis ultimately led to pinpointing interactions among the accountants, the AI innovation team, the accounting-information system with its various automatic elements, and the AI system. In addition, I was able to outline how these very different actors, the technologies, and their interactions had shifted over time and how those adjustments had, in turn, altered the routines and work roles. Accordingly, I depicted the composition of the socio-technical system via separate figures that reflect the pre- and post-implementation situation, thereby capturing the socio-technical evolution that had occurred.

With the data analysis for Essay 3, the first aim was to identify important events from the data, various practices functioning in the AI system’s development process, and the experiences of individuals. On this basis, it was possible to form a flow-oriented genealogical storyline for the emergence and unfolding of the system (and hence its algorithmic action) via the design and development work. Genealogy is a mode of accounting for history (Foucault, 1984) and of inquiry that aids in identifying those contingent correspondences that are, at base, fundamental to the process of ongoing (trans)formation. Thereby, it assists in teasing apart the dynamics of the conditions (Mousavi Baygi et al., 2021).

By conducting all the interviews and taking notes during and after each one, I immersed myself in the data and acquired extensive familiarity with the material’s nuances. Taking a flow-oriented perspective made it possible to perform preliminary analysis and create a detailed illustrative narrative of the case company’s socio-technical transformation. Taking the interview with the aforementioned data scientist as a starting point, I drew on the interview notes to begin weaving into the storyline how accountants’ experiences and perceptions had evolved over the course of the AI’s system’s design and development, with special attention to what they had emphasized as important moments/events along that path. Considering all the various views allowed me to form the overall storyline (Silverman, 2011), which I then examined from a flow-oriented perspective by looking at the three modalities of correspondence simultaneously with extracts from key informants’ interviews. This analysis process helped to reveal several distinct views of the overall (trans)formation. In a final check, all authors of the essay scrutinized the preliminary findings for possible inconsistencies.

3.4.2 Analysis in the case-study research

The data-analysis approach for the case study presented in Essay 2 reflects an abductive sensemaking process; analysis iterated between data and theory in a search for explanations to the phenomenon (Mees-Buss, Welch, & Piekkari, 2020; Sætre & van de Ven, 2021; van
Maanen, 1979). Two team members began by carrying out open coding (Strauss & Corbin, 1998) via ATLAS.ti software functions, assigning portions of the data set descriptive codes to capture relevant events and informants’ reflections on them. This afforded forming a rich narrative (Pentland, 1999) of the events that conditioned skill erosion at the case company.

Then, these two researchers reviewed each other’s codes by comparing them and discussing potential themes that might emerge in light of them. The resulting codes and related illustrative quotes, together with analytical interpretations, were presented to the rest of the team. Emerging concepts were reflected upon and debated at team level against the backdrop of literature on skill erosion and prior work on socio-technical elements (Alter, 2013; Sarker et al., 2019). While some concepts showed similarities to concepts from pre-existing theories, others appeared novel. For example, the essay’s authors identified three distinct facets of the work process in question.

In the next stage, examining the relationships among distinct socio-technical elements uncovered a connection between skill erosion and how mindfully each of the facets identified earlier had been handled. Throughout the analysis of informants’ responses (just as in the data collection preceding it), the researchers maintained healthy skepticism – since skill erosion usually occurs latently, the individual may well be unaware of it (Mees-Buss et al., 2020). Especially during the final interview round, any inconsistencies identified from earlier interviews were carefully discussed with the informants. Also, the team’s own interpretations were debated; testing them against the data, the team often tried to falsify them. Furthermore, material collected online aided in triangulation of the informants’ accounts of the automation system’s functions and specific events mentioned in the interviews.

The researchers then discussed the interim analysis results, to settle on a final coding structure that faithfully represents the data and communicates the interpretations. Moreover, our efforts to integrate the emerging concepts had yielded several provisional models. At this point, those models and our associated theories were tested – we considered them against the data and held full-team workshops to find plausible data-aligned explanations for the phenomenon of skill erosion. In the end, we integrated the concepts through a system-dynamics lens, since this aided in capturing the feedback loops and emergent outcomes that we had identified from the data. The abductive process (Sætre & van de Ven, 2021) directed our attention to the “shifting the burden” archetype, discussed below, as a potential anchor for theorization. That served as the nucleus as we began system-dynamics model construction that followed Senge’s (2006) guidelines on applying system archetypes. This systematic process yielded a model that offers a solid explanation of the phenomenon.

To test the relevance of the system-dynamics model for practice and be certain of its applicability beyond the empirical case in question, we employed applicability checks aligned with the recommendations of Rosemann and Vessey (2008). Passing these tests indicated that the model indeed addresses an important practical problem in an understandable way and also supplies insight that is actionable – i.e., that can be applied in practice.
4. Results

With this chapter, I situate the results presented in the three essays written on the basis of the two empirical data sets. The final section synthesizes the results by outlining the full picture of the key findings by means of the connections between the key findings described in the individual essays.

4.1 Essay 1

The aim with essay 1 was to advance understanding of critical socio-technical implications of cognitive technology’s implementation for roles in knowledge-intensive work. The essay deals with the shifts in dynamics of routines by which the AI deployment at the case company transformed work roles through altered division of tasks and responsibilities. The study revealed how the transformation process began a gradual shift of the accounts-payable accountants’ activities toward human–AI work. Thus, it answered the research question pertaining to how transition to such hybrid operations influences the roles in knowledge-intensive work through shifts in routines’ dynamics.

The project shed light on adjustments from the pre-implementation phase’s starting configuration (presented in Figure 1, below), in which the overall accounting process was arranged such that two separate groups of accountants focused on their respective parts of the work process. One of these groups, accounts-payable accountants, concentrated on processing purchase invoices (mainly manually), with the main task being to fill in postings for each purchase invoice; they were responsible for producing the correct postings before the monthly deadline for closing of the books. Unpacking the work role of an account-payable (AP) accountant further points to two routines within this main routine. Alongside the obvious one of validating purchase invoices via inferences from particular invoices’ information and drawing on domain knowledge to judge which account and VAT postings are appropriate for the given invoice, there is a routine that might escape notice – through validation-in-action, they were performing reflection in the moment to ascertain the correct posting. This important part of the AP practice reinforces the ostensive aspect and either maintains or expands the performative aspect of AP routines.

In the pre-implementation phase, the final validation of accounting-process outputs and reports was handled by general-ledger accountants, workers responsible for a wide range of activities, which encompassed (usually complex) daily work tasks, reporting on values, and communication with clients. These accountants monitored the correctness of the overall accounting process’s outputs and were accountable for their validity at a higher level.
Another important characteristic of the pre-implementation phase is the data scientists’ incomplete view of the AP routines. They lacked the domain knowledge necessary for moving beyond mainly the ostensive aspect. Although they attempted to overcome their knowledge deficit in the pilot stage (via the feedback and brief user observations), to a large extent the algorithms captured only ostensive elements of parts of AP routines. The situation had to change in the implementation phase, as the socio-technical configuration started to shift.

Soon after limited implementation brought exogenous change to routines, the major and minor problems besetting accounting work with selected clients brought a thorny issue to light. The erroneous auto-generated postings and high-volume misflagging under the AI system meant that something had to change. Firstly, AP accountants had to engage in greater reflection, which deepened their domain knowledge and enabled them to express it to others. The unintended temporary spike in this tedious, time-consuming activity highlights the essential role of validation-in-action. For their part, the in-house data scientists, whose performative-level understanding had improved little, continued their discussions with specific AP accountants. As they began to scrutinize the ML model and related algorithms, they were especially keen to understand a performative component: why some of the AP routines’ tasks vary in how they are handled. Through six months of gradual tuning, the material aspect of routines (the algorithms) grew able to capture the essence of the ostensive and performative aspects both. Most of the issues having been resolved, output accuracy rose significantly and the system could enter full production use.

After the tumultuous limited-implementation phase with its adaptive exogenous change, the AP accountants began to enact their routines locally in a new way to accommodate the new interactions and endogenous generative change in the human–AI hybrid routine. At this stage, a supporting formal element emerged in addition. The system’s permeation of AP practice brought adjustments to organization-level guidelines, accompanied by expectations that the accountants follow the new formal procedures.

Through such dynamics, the socio-technical configuration depicted in Figure 2 started stabilizing as the post-implementation phase continued. The new material aspect introduced in combination with the ostensive and performative aspects of routines began embedding itself deeply in the AP routines and the formal accounting process. Now, the AI system and the material aspect of routines brought with it are deeply anchored in hybrid form.

Figure 1. The accounting process and work roles before the AI system’s implementation.
The newly formed human–AI hybrid routine generates efficiency gains through time savings by automating the repetitive task of processing invoice data. With the AI system functioning as intended and the material aspect having taken over the performative dimension of the dynamics of routines, the general-ledger accountants receive a more real-time view of the financial situation of client companies (since many invoices are processed as soon as they enter the accounting-information system) and a higher-throughput AP process is possible. Because they no longer check high-confidence posting predictions, the AP accountants can concentrate instead on validating and correcting those predictions that do not reach the confidence threshold set.

Even though turnaround is faster in the new configuration, the AP accountants perform the same duties. While they are able to finish more client work per day, AP accountants’ worries about whether they might be starting to accept the AI system’s posting recommendations too readily (since the AI has begun to show consistent reliability) reveal that some vital shifts have occurred. The necessary validation-in-action routine that was part and parcel of the pre-implementation practice might be absent amid the augmentation of activities. Moreover, in this human–AI hybrid routine, moving the validation actions to the posting-validation report at the end of the formal AP process has brought changes to the validation-on-action routine as the AP accountants validate algorithms’ outputs by looking at abstracted values listed in a context-free report.

The socio-technical system configuration emerging after the AI system’s rollout has not entirely displaced the first but is gaining prevalence in the organization as the system’s production use exerts its influence more and more on the arrangement of routines and roles. Today, the AP accountants carry out the routine of supervising the performance of the AI system; by correcting low-confidence postings, they augment the ML model that augments their work. In addition to providing data from which the ML model can learn, they supervise the model’s performance. While they can deactivate the AI system’s use company-specifically if it performs poorly with a given client’s invoices, the system has become firmly embedded in operations. What the accountants interact with is one widget among many presented via the

**Figure 2.** The accounting process and work roles, transformed after the implementation.
user interface of the accounting-information system, which ties in with the material side of some of the earlier ostensive and performative routines.

Subtler shifts notwithstanding, the new socio-technical arrangements’ ascendency has not entirely escaped notice. As the uptake of the AI system brings changes in certain routines, it is subject to ongoing discussion about the accountants’ roles and related responsibilities.

4.2 Essay 2

From a system-dynamics standpoint, the second study explored the phenomenon of skill erosion in knowledge-intensive work with the objective of explaining how the degenerative effect occurs through over-reliance on cognitive technology – and possible ways to counter the negative dynamics. The essay, outlining the shift in system dynamics and the mechanisms through which skill erosion can take place in a knowledge-work organization, answers both research questions, involving how cognitive-automation systems can contribute to the erosion and what effects it might bring to an organization.

The study’s findings inform honing of the system-dynamics archetype referred to as shifting the burden (Kim, 1992; Senge, 2006), in the manner shown in Figure 3. The archetype expresses the notion that a problem’s symptoms need to be addressed by means of either symptom-treating or fundamental solutions (as Senge has noted, one should regard the two in relative terms, as different ways to address a given underlying problem). Because addressing the problem itself may be difficult or costly (Senge, 2006, p. 103), it is easy to resort to alternative (“symptomatic”) solutions that, while seeming highly efficient, have negative side effects: these both divert attention from the real problem and “cause the viability of the fundamental solution to deteriorate over time, reinforcing the perceived need for more of the symptomatic solution” (Kim, 1992).

![Figure 3. Adaptations to the “shifting the burden” framing.](image-url)

The two solution types form balancing loops (B1 and B2) that compete for dominance. In addition, leaning on a symptomatic solution gives rise to a side effect, thereby strengthening the reinforcing loop (R1) and weakening the fundamental solution. Though symptomatic
solutions are not purely negative and sometimes are needed, they should always be combined with fundamental solutions. The skill-erosion study took another caveat into account too: as Senge (2006) points out, the archetypes serve as a foundation for understanding how complex phenomena unfold, so they need to be adapted to the relevant study’s context.

The study in question applied a socio-technical approach to system dynamics in that it assumed the knowledge-work activities to be carried out in organizational settings and to involve dynamic and reciprocal interactions among human (social) and technological (technical) participants – interactions that influence and are influenced by organizational and environmental elements. With this setting, the archetype in Figure 3 was adapted to the study’s context through identifying the problem symptom of the burdensomeness of FAM, the fundamental solution of reducing the work’s burden via mindful conducting, the symptomatic solution of shifting the work burden by relying on automation, and the side effect of complacency. These were then applied as more general concepts connected with the archetype as Figure 4 illustrates.

Figure 4. A general system-dynamics model of skill erosion.

The burdensomeness factor at the heart of matters must be addressed by mindful handling of complex, time-consuming tasks and/or by shifting the burden to automation whereby reliance on automation arises. Shifting the burden does not eliminate the need for knowledge workers’ mastery of the work task, but it does alleviate the task’s burdensomeness.

The research team’s data analysis identified three facets of mindful operation: activity-awareness involving execution and supervision of task activities, competence maintenance that sustains domain competence, and output assessment guaranteeing that the outputs are correct and compliant with legislation. While handling all three facets mindfully requires effort and does not immediately render the work task less burdensome, one can become increasingly skilled and fluent over time, with enough repetition. This reduces the burden because the task becomes “automatic” (Senge, 2006, p. 153), though with a delay arising from the time it takes to learn the task more thoroughly. In the figure, mindful
Results

handling operates in a balancing **mindfulness loop** (B1) that reduces the burdensomeness of work tasks via skill accrual.

While mindful action is important for maintaining skills, it might not on its own constitute a practical solution. After all, cognitive technologies offer efficient ways to alleviate tasks’ burdensomeness. Shifting the burden to AI may immediately reduce the burden; however, as the error reductions and time savings brought by the system benefit the individual and organization alike, reliance on automation could grow excessive. This is understandable, since the knowledge workers experience less of a burden in these conditions. Automation reliance therefore represents the competing balancing loop – namely, the **reliance loop** (B2) – offering an alternative or complementary path for reducing the task’s burdensomeness.

The case company’s knowledge workers relied increasingly on the system, since it allowed them to focus their efforts on other tasks. Meanwhile, from the organization’s perspective, more work could now be done with the same human resources. The workers’ complacency amid this increasing reliance on automation entailed negative effects on all three facets, as manifested through decreased awareness of the task activities, deterioration of motivation to maintain and improve one’s domain competence, and evaporation of the previously rigorous approach to assessing outputs. Hence, the study identified **automation complacency** as the predominant potential negative side effect: the resulting assumption that there is no cause for concern (Moray, 2003; Parasuraman & Manzey, 2010) creates a risk of reduced incentives for mindful conduct by individuals.

The analysis suggests that decreasing mindfulness is bound to impair worker skills over time because lack of attention to the task both leads to forgetting what one has learned and discourages developing skills in response to possible environmental changes. Even though relying on automation apparently simplifies the work task, individuals’ complacency ultimately renders the work tasks increasingly complex over time as mindfulness declines. The state of complacency encourages a climate wherein skill erosion takes hold latently as long as the individuals do not need to apply their skills. The skill erosion becomes apparent only if a need for performing those work tasks again arises (e.g., when the cognitively oriented automation is discontinued or otherwise unavailable).

In the diagram, the effects of complacency taking stronger hold and reducing mindful conduct form a reinforcing loop, the **individual skill-erosion loop** (R1), whereby the work task grows more burdensome latently via skill erosion. In the end, a situation develops wherein individuals are bound to struggle with the task (or even with making sense of it, in the case of advanced erosion).

Drawing together all of the findings, Figure 5 articulates the study’s system-dynamics model of skill erosion. A fuller explanation of the erosion phenomenon demands factoring in not the core work-system elements but also various other constituent aspects of the organization’s socio-technical surroundings that interact with the central elements in the model. Analysis showed that the environmental factors of **legislation’s complexity** and **customer complexity** increased the burden from the work task, aggravating the underlying problem. As the automation improved **organizational performance** without creating observable negative consequences, **organizational complacency** grew. In a knock-on effect, the organization came to assume that it did not need to enforce its **skill-maintenance policies**, so the positive effect of skill maintenance on mindful conduct diminished more and more over time. It is possible that professional integrity expressed in **maxims of professionalism** (e.g., codes of conduct) could, in combination with
organization-level enforcement of skill-maintenance policies, outweigh forces of organizational complacency, though the case company did not display such dynamics.

Alongside the vicious circle articulated as reinforcing loop R2, the organizational skill-erosion loop, the analysis revealed a final element, at the level of the individuals involved. Their extreme mindless reliance on automation was further exacerbated by the advanced system’s high reliability (it rarely failed to perform the tasks correctly) and ability to handle task complexity (it was able to address all three facets of the work task, for instance). In addition, the system’s explainability features permitted a worker to fall back on system-provided explanations whenever requests for an explanation were received. Although the individuals could have used those features to make sense of how the system produced its outputs, thereby increasing the mindfulness of their conduct, they never put them to that purpose. In combination, these elements amplified loop B2 at the expense of B1.

![Figure 5. A comprehensive system-dynamics model of skill erosion.](image)

Beyond creating a comprehensive socio-technical model of skill erosion on the basis of these findings, the team examined where reversal of the erosion fits in the picture. We examined the events that ensued once the system’s decommissioning laid bare the skill erosion that had occurred latently and created an urgent need to restore the skills. At the level of individuals, immediate efforts included the accountants starting to go through old client materials, reverse-engineer the withdrawn system’s execution logic, and independently
study the system’s manual and domain-specific literature to bring their understanding to the level demanded by some relatively simple cases. The organization began to arrange internal workshops that involved resolving example cases, and mandatory training was arranged for the accountants. Moreover, managers directed the accountants to produce documentation that could serve as a reference guide for the work process in case needed. These efforts operating at both levels proved successful – both for the individual accountants, whose skill levels were clearly improved, and for the organization, which was able to reverse the degenerative dynamics.

The model facilitates concretizing the positive development too. Although B2 had previously dominated, loop B1 started gaining momentum as the dynamics shifted more in favor of mindful conduction. Although the organization kept using some cognitive technology, the adversities experienced left it conscious of the risk of skill erosion. Keenly aware of the need for better guarding against growing complacent, it demonstrated renewed determination to find a balance between automation reliance (B2) and mindful conduction (B1).

4.3 Essay 3

The final study was motivated by a desire to find explanations for the delays and other issues that readily beset the development, implementation, and use of an AI system. Investigating the case of a financial-accounting services company that had faced several delays to its design and implementation of an AI-based system, this longitudinal study tracked developments all the way through to successful deployment for full production use in the company’s work processes. To tackle the question of why AI system development and deployment projects for knowledge-work organizations experience delays, the research adopted a flow-oriented approach.

This represents an innovative technique. Instead of examining the AI system design and development as originating from the actors participating in it and as executed in interactions among them, the study was able to explore how the process of socio-technical formation and transformation gets dynamically shaped by the temporal conditioning of the flows of people and digital technologies (Mousavi Baygi et al., 2021). Taking this perspective to the fluid process of socio-technical (trans)formation permitted identifying the unfolding generative and degenerative dynamics in the process – whereby the practices and digital technologies acting in the process can favor or stifle meaningful action along the path. The essay approaches the results’ genealogical storyline from the angle of the three modalities of correspondence, thereby illustrating how the necessary conditions were formed for the AI system’s design and development practices, how the system came into being and continued to transform, and why it took nearly two years to bring the AI system into closer correspondence with the accounting practice.

The essay outlines how the conditions were created for the practices that began the design and development of the AI system and how the conditions affecting the practices at play continuously transformed in the course of that process. Secondly, it presents the central findings related to timing and timely seizing of opportunities, alongside how further possibilities for action were conditioned accordingly. The piece then tackles the role of attentionality and how being attuned to the flowing lines of action gives rise to conditions for sensing possibilities for action, before describing a final aspect: how undergoing a (trans)formative process opens new paths of becoming that furnish room for rediscovery and
reinvention by **actualizing** **(trans)**ormative opportunities. Together, the dynamics of these three modalities can bring about greater resonance among the flows, creating fertile ground for reaching convergence that aids in forming generative dynamics.

The findings point to appropriate conditions as necessary for even venturing onto the path to creating an envisioned AI system: suitable socio-technical conditions must be in place at the outset. For the case company, one major enabling historical development was a decision several years earlier to begin developing a cloud-based accounting-information system. Focusing on this system’s development was the key to beginning a transition from a largely paper-based flow of accounting data to a digital flow. Over time, the case company’s accumulation of structured data from its clients’ business transactions in the cloud-based system functioned in combination with other historical developments to create conditions that made a landmark decision feasible. The company could consider utilizing the data in training an ML model to make predictions for purchase-invoice bookings and even create an AI innovation unit.

Identifying important moments from the storyline facilitated making sense of timing and of seizing ripe opportunities. It sharpened the focus on how specific historical lines of action and their timely kairotic correspondences turned the idea of an AI system’s design and development into action. The storyline also brought out how the new innovation unit’s practice of design and development, in tandem with accountants’ feedback, conditioned the (trans)formation of these flows of action and led to deploying an AI system that sparked a new flow of algorithmic action. Thus, the findings reveal the centrality of timing for drawing contingent lines of action and their temporal qualities into stronger mutual alignment. For example, the data scientists’ delayed access to production data, by upsetting the timing, led to difficulties that rippled all the way through the accounting work because conditions did not exist for the algorithmic action to enter closer correspondence with accounting practice. While kairotic correspondences create new action possibilities, mistiming can impede convergence of the flows of action, thereby precipitating further delays to a system project.

Secondly, the findings clarified how exposure and attunement to the various flowing lines of action and their temporal qualities may give rise to conditions for sensing possibilities for action. I found that being attentive to temporal qualities such as rhythm can shape formation of correspondence, and this attunement itself can be a timely process. In contrast, if the AI system project’s schedule does not account for it, unexpected delays may arise. The findings thus accentuate the point that the picture is far wider than one of deliberate intention or planned goals for technology use. Since it is hard for project timetables to accommodate such potentially lengthy processes as attuning to sensing the possibilities for action, further delays might well ensue.

Lastly, the study revealed how the journey of undergoing (trans)formation opens new paths of becoming whereby one may rediscover and reinvent oneself. The innovation-unit personnel and accountants alike had to get exposed and attuned to the flows conditioning the (trans)formation connected with the AI system before they could sense timely opportunities. Both these sets of experts involved in the system’s design and development found themselves swept away and animated by the flows of action from time to time on the waves of the process of actualizing the new possibilities for action that had emerged. The study highlighted that, along the way, they were rediscovering and reinventing their paths of becoming to embody (trans)formative possibilities aligned with the corresponding flows. Forming these possibilities did take time, however, developing as the project developed. While creating
delays from the standpoint of the AI project, this was a necessary learning process for the individuals’ attunement with the other lines of action.

In sum, the findings demonstrate both the innovation unit’s and the accountants’ action possibilities as undergoing continuous (trans)formation throughout the design and development process. Though at first the AI system’s algorithmic action was disruptive to the accounting practice, it also created new possibilities for action, which the process then actualized. As the data scientists became animated by the accounting practice, the flow of algorithmic action itself was transformed. When that action began finding a shared temporal quality of rhythm and forming closer contingent correspondence with the accounting practice, it, in turn, began to condition and animate said practice.

Depicting the unfolding of the process, Figure 6 illustrates the four flows involved, with their temporal qualities such as rhythm. The diagram captures only confluence and kairotic timing among the main lines of action identified by the study. Line A represents the accounting practice, line B the flow of financial-transaction data, line C the ML models’ algorithmic action, and line D the AI system’s design and development practice. The storyline’s nexus points – the pivotal moments in shaping of the fluid (trans)formation process – are the pilot phase commencing (1), initial testing and limited production-environment use of the AI system (2), the design and development team gaining full access to the transaction database (3), and deployment for full production use (4).

![Figure 6. The kairotic meshwork of the AI system project.](image)

**4.4 The results in combination**

Together, the findings attest to the inherent complexity of socio-technical systems’ development when cognitive-technology implementations’ implications alter the dynamics. The dissertation project shed light on the shifts in dynamics that ensue as work practices and roles get transformed in such situations, alongside changes in the sets of skills required and the workers’ abilities to perform their tasks competently. Furthermore, the research highlighted how the deployment cultivates both intended and unintended beneficial consequences and ushers in detrimental outcomes too as new generative and degenerative dynamics begin taking shape in the socio-technical system.

Essay 1 provides important groundwork via a process perspective that facilitates examining the implementation of an AI system in connection with a knowledge-intensive work process.
Results

The study revealed how the implementation led to transformation of work roles as the effects of transition to human-AI work began rippling through the socio-technical system’s dynamics. The work draws attention to the disruptions to essential reflective routines that can accompany efficiency improvements. Furthermore, it highlights that, even though cognitive technology often is intended to make the work more meaningful, freeing the workers for richer, more rewarding tasks (Nedelkoska & Quintini, 2018) does not always follow. Awareness of the shifts and balances involved could prove vital to maintaining and improving domain knowledge appropriately amid the shifts entailed.

Delving more deeply into some of the dynamics involved via modeling of the forces at play within technology-influenced transformation, Essay 2 presents a comprehensive examination of the phenomenon of unintended skill erosion that develops latently over the years in consequence of over-reliance on cognitively oriented automation. Unpacking the complex dynamics influencing this detrimental skill erosion and its reinforcement, it presents specific mechanisms revealed by means of a holistic socio-technical approach. The piece further informs scholarship and practice by addressing how the dynamics may be reversed such that skill recovery takes hold.

Finally, Essay 3 completes the picture of balancing and looping processes by adding the layer of flows. The study reported upon, which addressed transformation’s complexities and experiences in connection with project delays plaguing an AI system’s development and deployment, reinforces the point that such projects are not purely technical endeavors – and that approaching them as if they were can cause problems. For suitable generative dynamics to unfold along the (trans)formative path, appropriate conditions must be achieved via the cascade of favorable historical conditions created through continuing, constantly developing achievement of suitable timing, attunement, and undergoing of the progressing process. The flow-oriented approach by which the study probed the dynamics (particularly temporal subtleties) presented in the other two essays is novel to the IS research domain. Therefore, the piece is rounded out with insight related to how to apply a flow-based approach in systems studies.
5. Discussion and conclusions

As the empirical research was in progress, mounting interest in cognitive technologies continued leading organizations to establish ongoing cognitive-technology initiatives and deployments, with recent years adding considerable thrust to AI-based initiatives for knowledge-intensive work, alongside the more stable demand for rule-based cognitive technology (Davenport & Ronanki, 2018). Hence, there is increasing pressure to understand and explain the various phenomena that unfold in the wake of cognitive technologies’ implementation in knowledge-work organizations’ business processes.

The overall contribution of the dissertation is to identify and advance understanding of how these implementations shift the complex dynamics of knowledge-intensive work’s practices and routines. By meeting the need for deeper study of the processes of automating and augmenting such work, the dissertation project connects the knowledge that attention to knowledge-intensive work’s changing processes can yield with awareness of the resulting shifts in socio-technical dynamics (bundling together intended and unintended outcomes and beneficial and detrimental results). This work forms a foundation for, in turn, deepening our knowledge of these novel cognitive technologies’ influence – on individuals and organizations alike – and questioning entrenched presumptions as to the ramifications for the relevant professions. The findings hold implications for both theory and practice, addressed, respectively, below. While the research had its limitations, these represent rich opportunities for future research, which are discussed in the final subsection.

5.1 Implications for theory

The three essays highlight how cognitive technology’s deployment in a knowledge-intensive work process begins to shift the patterns that condition the practices and activities in the socio-technical system for better or worse via generative and degenerative forces. Teasing out these dynamics is the first step toward fully comprehending them and developing tools for mitigating the degenerative dynamics/effects. The model of skill erosion presented in essay 2 represents the second step, modeling (here, conceptualizing elements that any efforts to balance the dynamics must attend to).

Underpinnings in socio-technical transformation theory offered a new perspective for this work and afforded greater conceptual clarity. Especially suitable for capturing how cognizance can develop (i.e., via growing attuned to the practices and algorithmic actions by undergoing the process) in a manner that enables sensing and initiating timely action, this backdrop highlights how a cognitive technology gets woven into the socio-technical fabric of an organization. Ultimately, theory that expresses this as a continuous achievement cultivates
profound awareness that any imbalance in tackling the system (e.g., focusing purely on creating something new, without maintaining prevailing crucial structures) can unstitch a portion of the fabric. In the case of unintended skill erosion, latent following of a vicious circle can lead to adverse consequences over time such that the only path remaining for meeting the work-role-linked responsibilities might be to commence an arduous reskilling process. Theory that renders dynamics of this nature explicit can form a backbone for understanding how organizations could cultivate the attentional orientation necessary for sensing when such patterns might become established and for supplying them with tools for continuous steering toward healthy generative dynamics.

Since the empirical studies were conducted in a financial-accounting setting, implications specific to scholarship in this field are worthy of special mention. In particular, Frey and Osborne (2017) have cited financial accounting as one of the professions likely to get hit hardest by automation. Although several tasks in financial-accounting work seem to be suitable candidates for application of cognitive technology (thanks to relatively low ambiguity of the interpreting and decisions – as in the case of processing FAM postings and even forwarding them to the tax authorities – and the work’s regulation-driven structure and rule-based nature), essays 1 and 2 do not support the notion that technology will render this profession redundant. Tasks’ automation and augmentation notwithstanding, human experts’ responsibility and accountability for the process and its outputs keep it in high demand. From this perspective, the dynamic of degeneration that cognitive technology can bring about, as highlighted in essay 2, points to precarious conditions for relevant organizations: if workers’ ability to perform the work process’s tasks competently is lost over time, the human experts end up only nominally in charge of the process. They might be perceived to be responsible and accountable, but it is the cognitive technology that runs the process.

The findings offer a contrasting perspective not just with regard to the effects of cognitive automation on the accounting profession but also in relation to the notion that cognitive technology will free human capacity for non-routine tasks more generally. Especially if the work role is narrowly specified, as in the case of the purchase-invoice processing examined in essay 1, the human experts could find themselves performing the same tasks, just more quickly; in terms of Sarker et al.’s (2019) concepts of instrumental and humanistic outcomes, narrow work roles with repetitive tasks are less likely to improve the humanistic outcomes than lead to intensification of work in specific parts of knowledge-intensive work processes as the arrangement yields intended instrumental outcomes such as better immediate organization-level performance. At the same time, signs of unintended outcomes such as little or no understanding among workers of how the cognitive technology operates could further undermine the planned transition and adjustment to human–AI work. The automation/augmentation lens in particular aids in comprehending such patterns. In conditions of apparently pure automation, human experts are left only superficially responsible, whereas an organization’s augmentation-oriented interventions could alter the dynamics in a manner safeguarding against potentially degenerative dynamics. This issue is relevant even when the scope of the human experts’ domain knowledge is much broader. In the case presented in essay 2, automation let the workers tend to more pressing issues as it relieved them of the cognitive burden of having to think through the FAM-related postings, but their skills still atrophied over time. Here too, a substitutive-automation approach led to both beneficial and detrimental humanistic and instrumental outcomes for the individuals
and organization. It is imperative to address the “dark side” behind the shining promise of an automation-based approach.

A key lesson is that increased efficiency typically comes at the expense of long-term mindful reliability. The dissertation project suggests that the knowledge-work organization’s individuals default to an automation-oriented perspective as the cognitive technology’s implementation triggers transformation of work practices and roles on several fronts. If the organization has not set up formal procedures for handling the technology from an augmentation perspective, the tasks and activities are bound to get externalized to cognitive automation wholesale, without recognition of any need to engage in cognitively burdensome rooting of activities that allow the human to remain in the loop. Therefore, readjustment of work roles and processes in pursuit of genuine human–AI work is a more demanding process than merely commencing to use the technology in line with earlier routines (see Grønsund & Aanestad, 2020). This pattern manifested itself clearly in the empirical cases studied. For instance, the cognitive technology took on some routines that accountants had carried out themselves, among them tasks that had fostered reflection-in-action; thereby, it sidelinied an important source of more seasoned experts’ informal skill maintenance and also created an opportunity for accountants with less experience to rely on algorithmic output. Thus, shifting to validation of algorithmic outputs led to a decline in informal learning via the reduced presence of reflection on the figures. Developments such as these starkly illustrate how readily the vision of augmenting a knowledge worker’s actions gets perverted into substitutive automation.

Accordingly, the overarching integrative insight that ties together the findings and implications from all the essays is that substitutive automation is liable to take root on account of humans’ local enactments in routines when guidelines and enforcement from the organization’s side are lacking. Without formal principles that steer the human experts toward augmentative use of cognitive technologies, they have no ready tools to refer to when adapting as the new technology enters use in specific parts of their work. When the individuals’ formation of new action patterns is influenced predominantly by a logic that emphasizes conducting the work efficiently by means of novel cognitive technologies, the human expert naturally adjusts to the circumstances at hand by adjusting the performative aspect of routines through a worker-specific sensemaking process. Without the organization’s proactive introduction of adjusted structure to the ostensive aspect of routines, the experts’ local enactments take precedence over any principles/rules that might otherwise steer them toward an augmentative, mindful approach to using the cognitive technology. In other words, by attuning to the institutional logic of efficient performance, the workers engage mindlessly with the material aspect of routines. As the ostensive and performative routines become embedded in the material aspect, the attention to speed to the exclusion of the dynamics that are unfolding severs important links in the action-pattern chain that could support learning and reflection. At the same time, the need to maintain that source of informal learning grows obscured. A false sense of remaining in the loop takes hold.

Recognition of these patterns highlights the criticality of the timing for introducing new procedures and principles. Considering this is fundamental to understanding cognitive technology’s use because it allows drawing attention to augmentative application whereby the human’s position in the loop is retained as the people involved begin to undergo the transformative process. Thus, my work supports D’Adderio’s (2011, 2014) contention that the way of implementing technological artifacts influences the very core of the execution and
change of routines, enabling routines’ transfer and contributing to their continuous transformation and evolution. However, the organization must deliberately guide this adaptation and transformation of routines if it wishes to reach the goal of dynamically forming task assemblages (Rai et al., 2019) by means of transitioning to human–AI work. Otherwise, the fertile ground will remain fallow. To support the appropriate enactment of the material facet of routines, formal practices must be set in place and enforced. All in all, cognitive-technology implementations require considerable attention to the formation and transformation of appropriate principles that aid in tuning local enactments of routines such that the desired outcomes follow (importantly, express goals such as efficient automation may be at variance with genuine long-term priorities such as augmenting the experts’ performance of their knowledge-intensive work tasks). The research conducted for this dissertation is valuable, then, for elaborating on the intricacies of how the dynamics of the implementations can unfold. The work advances scholarly knowledge not just by creating a more comprehensive picture of the mechanisms through which the dynamics unfold but also by forming a bridge between the literature on routine dynamics and automation–augmentation research. That bridgework allows researchers to take a relational approach whereby the unit of study is not individual agents but interactions of agents (agential technological artifacts included), thus answering Raisch and Krakowski’s call (2021) to explore the related phenomena relationally. Furthermore, with in-depth accounts of cognitive technologies’ implementation processes remaining scarce, the dissertation paints a much-needed vivid picture of their nuances in organizations at large and of how the dynamics that arise condition their enmeshment in the work practices and procedures, thereby leading to work roles’ transformation.

5.2 Implications for practice

The dissertation contributes to practitioner-oriented knowledge of the complexities in developing and implementing cognitive technologies for knowledge-intensive work and of the shift in the practice/routine dynamics that lie along the path of transforming work roles and skill requirements. Key findings from the study behind Essay 1 imply that humans can make local adaptations to their routines such that appropriate human–AI routines’ formation is hampered. In the absence of enforcement structures, transition to genuine hybrid, synergistic work gets thwarted, and the organization remains unable to reap such work-task assemblages’ full benefits. The study speaks to a need for managers to create procedures for steering toward proper routines of using the cognitive technology, making sure they take hold, and over time leading to solid established practice that applies an augmentation-based approach. Such mechanisms support using the AI system not for substitutive automation so much as in augmentation that creates opportunities for fruitful transition. Even organizations that have heretofore applied the former approach can thus support a move to human–AI work instead of human and AI work.

The findings reported from the study of skill erosion are consistent with prior work (e.g., Drummond, 2008; Garud & Kumaraswamy, 2005): Essay 2 clarifies that prioritizing short-term efficiency benefits over organizational learning may lead to detrimental outcomes in the long run. Therefore, organizations should plan ahead and formulate effective strategies for their introduction of cognitive technologies (Asatiani et al., 2019; Raisch & Krakowski, 2021), strategies that address both the existing practices, roles, and skills (which may have to
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change) and new ones. As applicability tests conducted to validate its practical utility confirm, the implementation model presented in Figure 5 should be able to assist managers in recognizing how cognitive technologies affect the dynamics of maintaining a healthy balance between automation and skills’ maintenance. Furthermore, the three facets of mindful conduction identified could serve as a helpful conceptual tool for arranging work with cognitive technologies. For example, a knowledge-work organization might take assessment of its employees’ current skill levels in terms of these facets as a starting point in devising appropriate skill-retention mechanisms. Both the model and the lens of the facets can inform managers’ focus further down the line also, as they gauge how the organization is faring in its efforts to find balance in using cognitive technologies in combination with employee skills.

With regard specifically to new projects for system development and implementation, Essay 3 offers insight into the delays and postponements that may well occur. Because an AI system’s implementation possesses potential to propel transformation of work practices, the organization requires time to “absorb” the novelty. Also, development of an AI system requires constant testing and tuning of its algorithms. While domain experts’ feedback and examination of the models’ performance facilitates this deductive work, temporal dynamics that condition future action alternatives may make this anything but a straightforward process. To foster and cultivate more favorable conditions, then, it is crucial to nurture ongoing communication and collaboration throughout the transformative. As the study revealed, any of numerous issues in steering the development practice for better correspondence with work-practice requirements could cause delays in the process.

5.3 Limitations and further research

Any research comes with its limitations. Firstly, some of the data analysis (especially for the studies behind Essays 1 and 3) was preliminary, and thorough analysis would reveal much more of the phenomena under study. For the case addressed in essay 1, where the focus was on unpacking various aspects of routines, ethnographic study could provide more nuanced data and richer understanding – of the performative aspect of routines in particular. Moreover, the data analysis that I conducted should be expanded to afford an in-depth account of the interactions, routines, and roles involved, alongside how all these evolved over time.

In the research presented in Essay 2, it was impossible to conduct a real-time longitudinal study that would have permitted directly observing workers’ skill maintenance and skills development (or lack thereof). The need to rely on a combination of cross-sectional interviews and retrospective longitudinal accounts by informants limited the efforts to uncover the skill-erosion mechanisms and construct a narrative of the events. Also, while the analysis created a holistic systems-oriented perspective on the phenomenon, it was impossible to dig into the process of skill erosion with finer granularity. Although the study uncovered why and how workers’ skills erode, it could not provide a detailed answer beyond articulating the general mechanisms modeled.

For future research, it might be possible to delve more deeply into the temporal dimension of the skill-erosion process and further break down the actions, decisions, states, and interactions through which skills gradually fade and disappear. Another possible avenue that stands out for future research is to expand understanding of the facets of mindful conduction that Essay 2 describes. Researchers could look more closely at the new concepts of
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competence maintenance, activity-awareness, and output control with specific attention to how these mediate both generative and degenerative effects on skills. Likewise, scholars interested in the metaskills that Essay 1 reveals to be pivotal for human–AI work could examine precisely how these aid in fulfilling specific responsibilities in settings of cognitive technologies. Finally, the flow-oriented research approach employed for the study behind Essay 3 represents a novel technique for the IS research field. Accordingly, future research could consider that approach in comparison with other socio-technical methods, probing the advantages and disadvantages of each.

Furthermore, although my work has provided a new window into how human experts may get cast out of the loop in the course of cognitive technology’s implementation and extensive utilization, this is an important phenomenon in its own right. There is much to be gained from looking at this process and its dynamics more closely. Doing so would help academia shed light on the important matter of how the human expert can remain in the loop and retain the necessary understanding of the algorithmic outputs involved. The topic of remaining in the driver’s seat will not go away any time soon.
References


