Machine learning in organizations: The processes of diffusion, capability development, and reframing

Tomasz Mucha
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Tomasz Mucha

A doctoral thesis completed for the degree of Doctor of Science (Technology) to be defended, with the permission of the Aalto University School of Science, at a public examination held at the lecture hall TU1 of the school on 29 April 2024 at 12:00.

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Abstract

The commercial diffusion of machine learning (ML) enables the development of novel and previously unattainable organizational capabilities. Over the past ten years, the rapid advances in ML algorithms, hardware, and tooling, increasing availability of data and computing resources, as well as highly publicized implementations of ML by tech giants and other firms have triggered and propelled further the diffusion of ML use in organizations globally. However, despite the relative ease of piloting ML projects, scaling and turning them into ML-based capabilities have proven to be challenging to the majority of organizations. The underlying reasoning behind this difficulty is the fundamentally different nature of ML development and updating. Unlike traditional information technology (IT), ML systems do not require explicit codification of task execution rules and their encoding by the developers into the inferential logic of the system. Instead, ML systems learn from data. This means that the existing approaches to traditional IT development are not enough for organizations to successfully build and keep up to date their ML-based capabilities.

Motivated by these challenges and the practical relevance of the problem, the overarching objective of this thesis is to explore how organizations can successfully develop and use ML-based capabilities by uncovering the underlying processes and how they unfold over time. The initial development of such capabilities starts with the organizational adoption of the novel technology. Therefore, to scope out the status of ML technology commercial diffusion, Essay 1 of this thesis explores the extent of ML use by large firms and how it has changed over time. Essay 2 concentrates on the process of ML-based capability development in individual organizations. It uncovers the mechanisms inhibiting and promoting the successful development of organizational capabilities based on ML. Finally, Essay 3 concentrates on the organizational processes required for an ML system to function in novel operating environments or application domains. The third essay, thus, unpacks the process of reframing an existing operational ML system.

This thesis contributes both theoretically novel and practically relevant insights into ML diffusion, development, and use by organizations. The promise of the transformative impact of ML – technologies which can learn from data and do not require explicit encoding of rules by humans – can be realized only if we advance our understanding of how organizations can productively harness these technologies. To this end, the thesis extends existing research by assuming an engaged scholarship approach and conducting in-depth longitudinal studies. The insights offered expand the understanding of organizational processes needed for the cultivation of ML-based capabilities beyond their initial development and implementation.

Keywords artificial intelligence, machine learning, organizational capabilities
Acknowledgments

After ten years of working in various roles in the industry, in 2019 I returned to university to pursue doctoral research focused on organizational adoption and use of machine learning technologies. The transition to academic work, learning the ropes, writing conference papers or articles, and eventually compiling and distilling my work into this thesis would not be possible without the support of many people I met throughout this process. While this brief section cannot fully express my gratitude towards them, I will at least attempt to recount selected thank you messages.

Two people played a critical role in my doctoral research journey - Associate Professor Robin Gustafsson and University Lecturer Timo Seppälä. I met them both a few weeks before sending my initial application to the doctoral program. They suggested that I choose which one of them would be my supervisor and which thesis advisor. The distinction between these official roles, however, had little practical implications – they both supported me in various ways and at different stages of my work. Timo encouraged me to take a learning-by-doing approach to research. Hence, we jointly carried out multiple smaller and bigger projects or studies and wrote and submitted working papers and articles. He has always been to me an inexhaustible source of new ideas, discussion and brainstorming partner, co-author, and mentor. Robin helped me choose the overall direction of my research work and keep the right ambition level and scope. I have learned from him a lot about challenging my assumptions, narrowing down the focus, and looking deeper into the problems I study to go beyond obvious interpretations. Robin has also introduced me to information systems (IS) as a research discipline, which became the primary research community I decided to contribute to. His guidance and feedback during the writing of my most recent essay and this thesis were critically important. Both, Robin and Timo have also inspired me to be entrepreneurial in my work and, at the same time, look for ways to be valuable for students, practitioners, and policymakers.

Next, I would like to thank my opponent, Professor Nicholas Berente, and two pre-examiners, Professor Margunn Aanestad and Professor Patrick Mikalef for spending their valuable time critically evaluating my work. It is my honor and privilege to have Professor Berente as my opponent. He has acted as a senior editor of the MIS Quarterly Special Issue on “Managing AI”, which is a key reference for all of my essays and my overall research work thus far. Furthermore, even though I have never met Professor Berente in person, I have been fortunate to learn from him thanks to his (and Professor Jan Recker’s) podcast on IS research. Both, Professor Aanestad and Professor Mikalef have also influenced my work and inspired developing two out of three essays included in this thesis.

I would like to thank Jane Seppälä, who has been to me an invaluable colleague and a fellow doctoral researcher. We both started our research projects around the same time and we both progressed at a similar pace. This means that we were able to share ideas and learnings along the way. We also shared a common interest in machine learning technologies and their impact on businesses. Therefore, I have been very fortunate to collaborate with her during our regular “AI Team” meetings (I am also grateful to Leena Pitkäranta, Kaisa Kukkonen, and Adam Berthold for joining us on some of those meetings), as well as work with her on a joint project leading to one of the essays in this thesis.
I am also grateful that I had a chance to work with and learn from Professor Kaveh Abhari and Assistant Professor Sijia (Catherine) Ma. Three of us met remotely during an academic hackathon (paper-a-thon) organized in association with the ICIS 2021 conference. We continued working together for many months, despite not meeting in person for a long time and living on three different continents. One of the essays included in this thesis is the result of our collaboration. Furthermore, Kaveh has been advising me and supporting me beyond the scope of our joint conference papers and articles.

Next, I would like to thank Professor Kalle Lyytinen. He has contributed to my development and the advancement of one of the essays included in this thesis. Professor Lyytinen has been leading by example – his knowledge, productivity, and overall diverse skillset have been inspiring for me and I feel extremely fortunate to be able to receive feedback from him on multiple occasions. His work has also solidified my interest in and appreciation of the sociotechnical systems perspective.

My initial decision to start this research project would not have happened without first securing access to an interesting and practically relevant business context. Therefore, I am extremely grateful to Alexander Törnroth and Antti (Jogi) Poikola for welcoming my participation as a (volunteer) team member of and contributor to Finland’s AI Accelerator. Working with both of them allowed me to not only collect key empirical data for this thesis but also be part of concrete efforts to keep the Finnish economy competitive.

My development as a researcher and subject matter expert has been grounded in the environment where I worked – the Department of Industrial Engineering and Management at Aalto University. Therefore, I feel fortunate that I had an opportunity to learn from professors, lecturers, and many wonderful colleagues who made my work at the department interesting, mentally stimulating, and rewarding.

Furthermore, as a member of the Aalto community, I have greatly benefited from very welcoming and encouraging interactions with the faculty and researchers working at Information Systems Science at Aalto University School of Business. I would especially like to thank Professors Matti Rossi, Virpi Tuunainen, and Esko Penttinen.

I would also like to thank wonderful and curious people who have been inspiring, educating, and keeping me up to date with the developments in AI through their roles as podcast hosts. It is amazing how much I feel I know them, even though I have never met any of them in person. The work of these people and listening to countless hours of audio recordings of their discussions, reflections, or interviews with guests have greatly contributed to my understanding and appreciation of how little I know. In no particular order, I would like to thank Andy Ilachinski and David Broyles (AI With AI – the podcast is not running anymore, unfortunately), Chris Benson and Daniel Whitenack (Practical AI), Daniel Faggella and Matthew DeMello (AI in Business), Sam Charrington (The TWIML AI Podcast), Craig Smith (Eye on AI), Lex Fridman (Lex Fridman Podcast), Joanna Penn (The Creative Penn Podcast), and, as already mentioned, Nicholas Berente and Jan Recker (this IS research).

My family has also been extremely supportive and understanding throughout the past 5+ years. My wife, Tarja, in many situations, sacrificed her own time and energy by assuming an enormous share of responsibilities at home to allow me to work and progress with my research. To a large extent, she has been the invisible enabler of this doctoral thesis. My two sons, Joonas and Alex, also have played an important role throughout this research. On the one hand, the urge to gain insight into what skills and knowledge my boys will need in their future, where AI is deeply integrated into most of what people do, has been motivating me to work harder. On the other hand, being present today, participating in and experiencing how they grow and develop forced me to detach from research. These two opposing forces shaped my work and will continue to do so.

Finally, I would like to express my gratitude to Yrjö & Senja Koivunen Foundation and Aalto University Department of Industrial Engineering and Management for the financial support I received.
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References

Full-length essays
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<th>Description</th>
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<tr>
<td>AI</td>
<td>artificial intelligence</td>
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<tr>
<td>ASR</td>
<td>automatic speech recognition</td>
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<td>df</td>
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<td>FAIA</td>
<td>Finland’s AI Accelerator</td>
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<td>IS</td>
<td>information systems</td>
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<td>IT</td>
<td>information technology</td>
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<td>ML</td>
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List of essays

This doctoral thesis consists of a summary and of the following essays which are referred to in the text by their numerals.


Author’s contribution

**Essay 1:** AI Diffusion Monitoring among S&P500 Companies: Empirical Results and Methodological Advancements

Leading author and project lead. Main responsibility for all aspects of the study including data collection, development of the procedure for qualitative content analysis, management and coordination of analysis work conducted jointly with a research assistant, implementation of Python and R code for data collection and analysis, literature review, and writing. Joint development of the research idea together with Timo Seppälä. Timo, furthermore, provided feedback and support during the analysis and writing.

**Essay 2:** Riding a Bicycle While Building Its Wheels: The Process of Machine Learning-Based Capability Development and IT-Business Alignment Practices

Leading author and project lead. Main responsibility for all aspects of the study including research idea development, securing access to the primary study setting, data collection, data analysis, literature review, and writing. Joint development of the theoretical framing, conceptual model, manuscript writing, and revisions together with Sijia Ma and Kaveh Abhari. Ma, furthermore, conducted two interviews (approximately 2% of the empirical material used in the study).

**Essay 3:** Reframing Machine Learning Systems through Data Work: A Case Study of a Medical Transcription Company

Leading author and project lead. Together with Jane Seppälä joint responsibility for all aspects of the study including research idea development, securing access to the case company, data collection, data analysis, literature review, theoretical framing, formulating contributions, and manuscript writing. Robin Gustafsson and Kalle Lyytinen provided feedback and support during the design of the second phase of data collection (approximately two thirds of the empirical material), data analysis, development of theoretical framing and contributions, and writing.
1. Introduction

1.1 Background synopsis

The fact that there is AI in the middle is almost unimportant. The point is now the customer has got a capability they did not have before, which we have made work by understanding the technicalities of AI, the way that the AI works, all the complexities of actually embedding it in the system, getting the human in the loop, and putting it all in front of the customer in a way that makes sense to the customer.

Digital Engineering Lead
Interview transcript

The opportunities brought by machine learning (ML) technologies are vast, but the processes of creating and using organizational capabilities which are based on ML technologies are fraught with challenges. As the opening quote shows, practitioners face a variety of difficulties when developing ML-based capabilities. The commercialization process of ML technologies extends beyond technical problems. Indeed, it involves complex relationships between social and technical dimensions of organizational capabilities (Asatiani et al., 2021; Lyytinen et al., 2020; Mikalef & Gupta, 2021; Raisch & Krakowski, 2021). The root cause of these challenges is the fact that ML systems learn from data and do not require explicit codification of how to perform their intended tasks (Brynjolfsson & Mitchell, 2017). This makes them distinct from any other IT technology thus far (Berente et al., 2021; Lyytinen et al., 2020), including previous generations of artificial intelligence (AI), such as expert systems (Berente et al., 2021). Consequently, relying on existing organizational and software development approaches is not sufficient to successfully build and operate ML systems (Lwakatare, Raj, et al., 2020; Paterson et al., 2021) as an integral part of organizational capabilities. Hence, we need to develop an understanding of organizational processes for taking ML technologies into use, developing capabilities based on these technologies, and reframing the underlying ML systems to adapt them to inevitable changes in the operating environments or application domains.

The reasoning behind the widespread organizational drive to build, deploy, and leverage ML is manifold. First, the performance of ML technologies has been increasing rapidly in recent years. Landmark achievements that illustrate this advancement include the first use of GPUs (graphics processing units) to train artificial neural networks; the victory of IBM Watson in Jeopardy; the domination of ImageNet image classification contest by deep neural networks; AlphaGo winning in Go against Lee Sedol (Chui et al., 2018); DeepMind releasing in 2018 AlphaFold, which achieved state-of-the-art performance on several protein structure prediction benchmarks (Heaven, 2020); and finally OpenAI releasing a series of GPT models for generating human-like text (Bubeck et al., 2023). Second, these technological advances, have been followed by widely publicized ML success cases from tech firms, such as Google (Knight, 2018), Amazon (Sahni et al., 2017), Netflix (Gomez-Uribe & Hunt, 2016) and, most recently, OpenAI and Microsoft, which released ChatGPT – the first consumer application in the history to reach 100 million users within two months since its release (Milmo, 2023). Third, apart from increasing awareness, these advances were associated with a growing availability of infrastructure for training and serving ML systems and proliferation of both open-source and proprietary
ML algorithms, services, and tooling. Next, with the increasing digitalization, organizations continued to collect more and bigger variety of fine-grain data which is essential for ML training (Strickland, 2022). Last, but not least, ML systems can be used in organizational settings to automate task execution or assist people via augmentation in a variety of tasks (Raisch & Krakowski, 2021), many of which could not be feasibly addressed with traditional IT only (Davenport & Ronanki, 2018). This unlocks a massive potential to increase the productivity, efficiency, sustainability, and competitiveness of many organizations (Berente et al., 2021; Brynjolfsson & Mitchell, 2017; Plastino & Purdy, 2018; Schoormann et al., 2021). The combination of these developments creates a positive feedback loop, which attracts an increasing number of organizations to try to benefit from the emerging technological opportunities (Bransnahm, 2010).

Fueled by these developments, the diffusion of ML technologies into organizational use continues to unfold, with a large share of organizations attempting to create an increasing range of ML-based capabilities (Maslej et al., 2023, sec. 4.3). While a handful of high-profile tech firms spearheaded the commercial implementation of ML, many (potential) use cases, often more mundane, emerged across a variety of industries. For instance, organizations have been developing, piloting, and implementing ML in a variety of settings, such as investing (Ge et al., 2021; Sturm, Koppe, et al., 2021), predictive policing (Waardenburg et al., 2022), patient treatment in hospitals (Lebovitz et al., 2021), recruitment (Trocin et al., 2021; van den Broek et al., 2021), consumer lending (Strich et al., 2021), analysing routes of cargo ships (Gronsund & Aanestad, 2020), creative design consulting (Trocin et al., 2023), and fraud detection (Asatiani et al., 2021). This breadth of operating environments and application domains is in line with the view that ML is a general-purpose technology with a high business impact potential (Brynjolfsson & Mitchell, 2017; Bubeck et al., 2023), which further exacerbates the need to understand how ML technologies diffuse into organizational use. The urgency of developing insight into the processes of ML adoption and use in organizations is underlined by not only the vast opportunities brought by these technologies but also by the significant challenges that organizations are up against when building and using ML-based capabilities.

Even though ML projects can be piloted with ease, converting them into organizational capabilities by scaling, deploying, and operating in a daily business context has turned out to be a difficult process (Benbya et al., 2020; Lwakatare, Raj, et al., 2020). Many organizational efforts around ML never progress beyond the pilot or proof-of-concept phase (Benbya et al., 2020). This results in as little as 10% of companies generating meaningful business value out of their ML initiatives (Ransbotham et al., 2019). Furthermore, when implemented, ML technologies might lead to or reinforce negative outcomes, such as unfairness, bias, or inequality (Vinuesa et al., 2020). Despite these practical challenges, ML has earned a reputation as one of the most sought-after technologies by businesses globally (Davenport & Ronanki, 2018).

Motivated by the vast opportunities for ML technologies to impact business and society, and equally substantial challenges, IS and organizational scholars have proposed research agendas calling for in-depth investigation of ML in organizations (Benbya et al., 2021; Berente et al., 2021; Faraj et al., 2018; Lyytinen et al., 2020; Raisch & Krakowski, 2021). While the research community has actively responded to these calls, many important questions falling under this broad umbrella topic remain unanswered or only preliminarily investigated (Ågerfalk et al., 2022). Research on how organizations take ML technologies into use, develop capabilities based on these technologies, and adapt the underlying ML systems to inevitable changes is still only emerging. The organizational adoption of ML technologies and their subsequent management are complex because of the cyclicity of ML development and use, feedback loops, and the evolving nature of ML (Mucha et al., 2022b; Raisch & Krakowski, 2021). Since ML systems can change over time through retraining based on new data and without modification of the software code (Lyytinen et al., 2020), which creates closed-box or inscrutable models, these systems enjoy higher levels of agency than other IT systems (Berente et al., 2021). Hence, when ML systems enter organizational use, they frequently change the roles, routines, or responsibilities of employees (Gronsund & Aanestad, 2020; van den Broek et al., 2021; Waardenburg et al., 2022). This is especially the case when ML systems take over a substantial share of tasks carried out by some groups of employees (Gronsund & Aanestad, 2020; Strich et al., 2021). These insights concur with the view that to advance our understanding of ML systems in organizations we need to recognize that ML systems require cultivation within organizations.
(Lyytinen et al., 2020), which unfolds over time. Hence, we need to uncover the underlying organizational processes through longitudinal studies (Mikalef & Gupta, 2021).

Assuming a perspective which puts the unfolding of organizational processes and underlying mechanisms into the front stage provides an opportunity to extend the current scholarly conversation on ML in organizations (Ågerfalk et al., 2022; Lyytinen et al., 2020; Raisch & Krakowski, 2021). For instance, studies concerned with the diffusion of ML into organizational use rely primarily on point-in-time surveys or simple keyword count methods, thus oversimplifying the complex nature of organizational processes for technology adoption (Rogers, 2010) and rapid changes in ML use. Next, the emerging research on ML-based organizational capabilities shows that building such capabilities relies on the capacity of organizations to not only develop ML-related resources – tangible, human, and intangible – but also integrate and orchestrate them to form capabilities that can be leveraged in business activities (Mikalef & Gupta, 2021). However, the understanding of how these initiatives unfold over time and what mechanisms shape their outcomes is still missing (Mikalef et al., 2023; Mikalef & Gupta, 2021). Empirical studies conducted thus far, and which take a process perspective (e.g. Grønsund & Aanestad, 2020; Ruissalo et al., 2022; van den Broek et al., 2021) provide only a starting point because they concentrate on the initial system development and implementation stages. Thus, they leave out the subsequent operation and adaptation, which are essential, given that most ML systems create value not as one-off projects, but rather over extended periods (Shollo et al., 2022). Therefore, existing studies fall short of uncovering the role of organizational processes beyond the initial implementation and how they translate to ML system cultivation, particularly concerning data and retraining (Lyytinen et al., 2020).

This thesis is set within this broader context and aims to contribute both theoretically novel and practically relevant insights into how organizations take ML technologies into use, develop capabilities based on these technologies, and adapt the underlying ML systems to changes. The promise of the transformative impact of ML can be realized only if we advance our understanding of how organizations can productively harness these technologies in their daily operations. The rest of the thesis is organized as follows. In the remainder of the introduction, I outline the scope and objectives of the thesis, as well as clarify the key concepts used and lay out my assumptions and philosophical stance. Section 2 provides a more encompassing theoretical background, where I discuss the rise of ML and the associated challenges. Thereafter, in Section 3, I present the essays included in the thesis – their data, methods, and findings. In Section 4, I discuss the implications of my research to theory and practice and indicate how these insights might guide future research on ML in organizations.

1.2 Scope and objectives

The overarching objective of this thesis is to explore the processes of how organizations can successfully develop, use, and cultivate over time ML-based capabilities. The research results extend the emerging theoretical understanding of ML in organizations and have implications for practitioners who are tasked with building and using ML systems in their daily work. To meet this objective, I conducted three empirical studies, which I present here. Table 1 provides an overview of the thesis scope.

The progressive logic connecting the three essays is as follows. In the first essay, I scope out the extent of ML technology commercial diffusion across different organizations by engaging in exploratory analysis. Apart from grounding the thesis research in the broader empirical context of ML in organizations, this study provides insight into the extent of ML use by large US firms and the pattern of changes in the diffusion rate over time. To meet the objective set out for Essay 1, this study involved also methodological development. The need for such development arose from the shortcomings of existing content analysis approaches used in technology diffusion research, which primarily rely on simple keyword analysis. Thus, these methods do not account for the multiphase nature of organizational adoption of complex digital technologies. Accordingly, the first research question in Essay 1 was:
<table>
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<th>Essay 1</th>
<th>Essay 2</th>
<th>Essay 3</th>
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<tr>
<td><strong>Overarching research objective</strong></td>
<td>To explore the processes of how organizations can successfully develop, use, and cultivate over time ML-based capabilities</td>
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<tr>
<td><strong>Contribution towards the overarching objective</strong></td>
<td>Scoping out ML technology commercial diffusion across different organizations – the extent of use and how it has changed over time</td>
<td>Uncovering the mechanisms inhibiting and promoting the successful development of organizational capabilities based on ML technologies</td>
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<td><strong>Research question(s)</strong></td>
<td>RQ1.1: How to extend content analysis methods for technology diffusion monitoring to account for multiple phases in the adoption of technologies into commercial use by organizations? RQ1.2: How have machine learning-based technologies diffused across different organizations?</td>
<td>RQ2: What mechanisms facilitate the development of machine learning-based capabilities?</td>
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<tr>
<td><strong>Background literature</strong></td>
<td>Diffusion of innovations, technology adoption, and firm population-level analysis</td>
<td>Organizational capabilities, Machine learning operations, IT-business alignment</td>
</tr>
<tr>
<td><strong>Empirical scope and level of analysis</strong></td>
<td>Population of firms represented by a large sample, industry- and firm population-level analysis</td>
<td>Multiple organizations; organizational-level analysis</td>
</tr>
<tr>
<td><strong>Research design and methodology</strong></td>
<td>Empirical, Mixed methods; qualitative content analysis and coding; and quantitative exploratory diffusion analysis</td>
<td>Empirical; case study analysis; qualitative analysis and coding</td>
</tr>
<tr>
<td><strong>Data and sources</strong></td>
<td>Public; transcripts of management presentations to investors (n=2047); 500 largest US listed companies; covering 2004-2019 period</td>
<td>Participating organizations (n=44); participatory observation events (n=123); interviews (n=26); internal archival documents (n=62); collected over 4-year-long period</td>
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<tr>
<td><strong>Key results and insights</strong></td>
<td>Exploration and visualization of ML technology diffusion among S&amp;P500 companies A novel method for monitoring the diffusion of technologies at the commercial lifecycle stage Validation of the proposed method against selected theoretical predictions based on past research on technology diffusion</td>
<td>ML-based capabilities (MLbC) consist of three cycles – ML Organization, ML Technology, and ML User - which need to be aligned The alignment unfolds progressively and iteratively through three phases – (Re)Initiation, Effectuation, and Sustaining This process is governed by the interaction of two pairs of Structural Characteristics of MLbC (Temporal Complexity and Context Sensitivity) and Alignment Practices (Fostering Temporal Congruence and Cultivating Organizational Meta-learning)</td>
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RQ1.1: How to extend content analysis methods for technology diffusion monitoring to account for multiple phases in the adoption of technologies into commercial use by organizations?

The resulting proposed method is based on content analysis, yet it better reflects the non-binary nature of ML adoption by organizations. The insights from this study bring value because ML technology commercial diffusion patterns and status have been difficult to ascertain due to a lack of methodological transparency or oversimplification of the organizational processes of technology adoption in earlier studies dealing with the topic. Having developed the proposed method, I was able to address the following question in the same essay:

RQ1.2: How have machine learning-based technologies diffused across different organizations?

The sample of companies investigated in this study consisted of the largest publicly listed companies in the United States. These companies have been among the most prominent and visible adopters of the technology. Thus overall, this essay proposes a new method and illuminates the temporal pattern of ML commercial diffusion among large firms.

To go beyond diffusion patterns at the level of firm population and uncover insights into the organizational-level processes governing ML-based capability development and use, the remaining two essays rely on qualitative analysis and longitudinal in-depth case studies. In Essay 2 I investigate the following research question:

RQ2: What mechanisms facilitate the development of machine learning-based capabilities?

Essay 2 relied on a data set collected over a four-year-long period and primarily through participatory observation at Finland’s AI Accelerator (FAIA). This data is also extended by additional follow-up interviews with practitioners outside of FAIA and located not only in Finland. Essay 2 provides a theoretical explanation of the organizational process for the development of ML-based capabilities (MLbC). The analysis uncovers two structural characteristics, which make MLbC development challenging. These characteristics are Temporal Complexity and Context Sensitivity. Organizations, which were successful in developing and maintaining MLbC relied on two sets of organizational practices to overcome the inhibiting structural characteristics. These practices were Fostering Temporal Congruence and Cultivating Organizational Meta-learning.

In Essay 3, I concentrate on one of the identified structural characteristics of MLbC inhibiting its alignment – Context Sensitivity. This characteristic denotes “the high vulnerability of MLbC to changes that might take place in the task where ML system is used (e.g., specific business process), organization (e.g., changes in the team developing ML model), or its external environment (e.g., market)” (Mucha et al., 2023, p. 194). Such changes frequently undermine ML system performance and make these systems unreliable or, depending on the use context, even dangerous. Hence, when the operating environment or application domain for an existing ML system changes, then that system needs to be reframed to retain its performance. Therefore, in Essay 3 I ask:

RQ3: How do organizations reframe their operational ML systems through data work to retain ML system performance?

Essay 3 deepens the insight into organizational data work, which is needed to reframe ML systems and, thus, tackle context sensitivity highlighted in Essay 2. This study relies on an in-depth single case study of a medical transcription company. The case company had a five-year-long track record of utilizing its proprietary ML-based system for speech recognition. During that time, it had to continually reframe the system in response to changing business needs, including expansion to new languages, medical specializations, and application domains. The
case organization engaged in four types of data work to reframe its automatic speech recognition system: (1) generating training data, (2) establishing data quality and coherence, (3) spotting out-of-frame data, and (4) addressing data gaps. Furthermore, to succeed in reframing they had to constantly balance two aspects of data work – control over it and its efficiency.

1.3 Definitions of key concepts

The purpose of this section is to provide the reader with a glossary and clarify some of the terms that might have multiple or contested meanings. The terminology discussed here appears throughout this study, thus familiarity with these concepts is essential to understanding the content of the thesis. Scholars frequently consider technology diffusion as synonymous with innovation diffusion (Rogers, 1983, p. 12). Given the focus of this thesis on ML technologies and organizations as adopters of the technology, I rely on the definition of diffusion proposed by Fichman (2000, p. 1), which states that it is “the process by which a technology spreads across a population of organizations”. It is important to recognize that the adopters, in this case, are not individuals, but rather organizations. Such qualification elevates the importance of understanding the sociotechnical nature of diffusion, where the technology, adopting organization, and its environment meaningfully influence the unfolding of the diffusion process (Tornatzky et al., 1990) and the degree of subsequent technology adoption within the focal organization (Cooper & Zmud, 1990; Rogers, 2010).

Helfat and Peteraf (2003, p. 999) define organizational capabilities as “the ability of an organization to perform a coordinated set of tasks, utilizing organizational resources, for the purpose of achieving a particular end result.” In this thesis, I rely on such conceptualization as it has earned a long cumulative tradition and continues to be used in organizational sciences (Helfat et al., 2023) and IS (Steininger et al., 2022) research. Furthermore, it continues to be relevant and applicable to present research on ML in organizations (Helfat et al., 2023). This view of organizational capabilities is distinct from ad hoc execution of tasks or performance of activities in organizations (Helfat et al., 2009, p. 5). Instead, capabilities are a result of experience, which is accumulated over time (Amit & Schoemaker, 1993; Bharadwaj, 2000). Thus, capabilities represent routine or practiced activities (Winter & Nelson, 1982, p. 14) that work in a reliable and repeatable manner (Helfat & Peteraf, 2003). This conceptualization of capabilities implies also that capabilities are “not simply a skill of a single individual or feature of a single machine, or an ability to access market opportunities in a straightforward way” (Helfat & Winter, 2011, p. 1244). Rather, organizational capabilities necessarily require the combination and utilization of multiple resources, including tangible, human, and intangible ones (Grant, 2016, pp. 118–123). Overall, this perspective prescribes capabilities as an essential role in determining organizational competitiveness and performance (Sirmon et al., 2007).

Artificial intelligence is a concept which requires a definition and a commentary, due to its contested and evolving nature. The work of Marvin Minsky, who was one of the pioneers of AI research, serves as a useful starting point. Minsky (2007, secs. 4–2.1.) coined the term suitcase word, “which we each fill up with far more stuff than could possibly have just one common cause.” AI is such a suitcase word with many meanings attributed to it by various disciplines, scholars, and over time (Nilsson, 2009, p. 13). In this thesis, I rely on the definition proposed by Berente and colleagues (2021, p. 1435) stating that AI is “the frontier of computational advancements that references human intelligence in addressing ever more complex decision-making problems”. Given that the frontier changes as the underlying technological solutions change, this thesis focuses on a particular subset of AI, which is machine learning. Before defining ML in greater detail, it is still important to recognize that the rhetorical practices of practitioners are not bound by strict limits set by definitions of scholarly concepts. This means that practitioners might use AI and ML interchangeably. This is particularly the case within the period during which I collected empirical data for this thesis. Therefore, AI as a term might frequently appear, while having the underlying meaning of ML, which I cover next.

Machine learning represents the present wave of AI (Berente et al., 2021) as it “has emerged as the method of choice for developing practical software for computer vision, speech recognition, natural language processing, robot control, and other applications” (Jordan &
ML is a broad set of techniques for creating computer systems in a way that is fundamentally different from the approaches to developing traditional IT (Brynjolfsson & McAfee, 2017). ML models are derived from training data sets through training (learning) procedures, which aim at identifying patterns in the data (Paterson et al., 2021) and, through that experience, allow ML systems to improve automatically (Jordan & Mitchell, 2015). This approach to creating ML systems can be further divided into supervised, unsupervised, and reinforcement learning (Ailisto et al., 2018). Generative AI systems, such as ChatGPT, may rely on a combination of approaches including self-supervised learning – “the pretraining task derived automatically from unannotated data” (Bommasani et al., 2022, p. 4) and reinforcement learning with human feedback (Dwivedi et al., 2023).

**Machine learning-based capability (MLbC)** is a specific type of organizational capability which rests on the ability of an organization “to align ML-specific and other resources to perform a particular organizational activity (set of tasks) in a reliable, repeatable, and value-added manner” (Mucha et al., 2023, p. 194). This view of MLbC is congruent with the definition of AI capability proposed by Mikalef and Gupta (2021), although I restrict its scope to the present wave of AI only – that is ML – because of the inherently dynamic, evolving, and uncertain meaning of AI as a frontier of computational advancements (Berente et al., 2021). Importantly, my conceptualization of MLbC necessarily involves practiced and routinized involvement of organizational actors, thus aligning the MLbC concept with the notion of organizational capabilities and distinguishing it from purely stand-alone capacities of technology (e.g. ML-based features embedded into products).

### 1.4 Assumptions and philosophical stance

The purpose of this section is to discuss the assumptions and philosophical stance, which I took in my work. Similarly to the understanding of key concepts presented in the previous section, familiarity with my conceptual departure points aids in the critical evaluation of my research and appreciation of its contributions.

This thesis assumes an engaged scholarship approach, which is grounded in critical realism (Van de Ven, 2007). Engaged scholarship aspires to meet “the dual hurdles of relevance and rigor for theory as well as practice” (Van de Ven, 2007, p. 6). It is concerned with complex problems, particularly in the context of organizations and management, and how to generate insights and knowledge about them through participative research. The engaged scholarship aims to achieve this goal by tapping the diverse perspectives of multiple and relevant stakeholders in the research process, most notably researchers and practitioners. While there are several alternative forms for practicing engaged scholarship (Van de Ven, 2007, pp. 269–271), I utilized informed basic research in Essay 1 and collaborative research in Essays 2 and 3. Since I consider Essay 1 a scoping study for my work, my detached and outsider approach was justified. The subsequent essays, however, required much deeper engagement with practitioners to co-produce knowledge. I believe that assuming a more collaborative and insider mode of conducting research was the right approach to gain nuanced and fine-grained insights, which are both theoretically interesting and meaningful for practitioners.

Critical realist ontology (Bhaskar, 2013), which I assume in my work, views reality as existing independently from our mind or ability to perceive or describe it. Furthermore, there are three layers, or domains, real, actual, and empirical. The first layer consists of foundational structures, such as “social structures, natural objects, material artefacts, and conceptual entities such as language, opinions, and goals” (Volkoff & Strong, 2013, p. 820). Many of these structures might not be detectable by human observers or, even more broadly, any direct measurement attempts. The domain of actual arises from mechanisms acting on the structures and it includes events and outcomes. However, we might not be able to observe all these outcomes either. Rather, what is directly accessible to us is the domain of empirical. Thus, to advance with the important task of uncovering mechanisms (Hedström & Swedberg, 1996; Hedström & Ylikoski, 2010; Volkoff & Strong, 2013), which might be only partially visible, and to aid with answering questions about how and why things happen, scholars embracing critical realism appreciate the plurality of methods and abductive reasoning (Van de Ven, 2007, Chapter 2). Accordingly, my work relies on multiple methods, empirical settings, and triangulation...
through the analysis of alternative sources. Furthermore, I consider that abductive reasoning gave me conceptual freedom to not tie my work to a single theoretical lens or perspective only.

In my enquiry, however, I build on the sociotechnical system perspective (Bostrom & Heinen, 1977; Emery, 1993; Leavitt, 1965; Sarker et al., 2019; Trist & Bamforth, 1951) as a conceptual departure point for developing theoretical insights. Given that conceiving a theory in engaged scholarship practice is a theory-laden effort (Van de Ven, 2007, Chapter 4), sociotechnical framing was instrumental in helping to identify potential elements included in the domain of real–task, technology, actor, and structure – which I needed to consider. I, furthermore, view this conceptual departure point as useful because of three reasons. First, sociotechnical systems theory was born in times of rapid technological advances transforming work and organizations (Trist & Murray, 1993). Now, with the diffusion of ML into organizational use and the resulting changes, we can benefit from the sociotechnical perspective which is sensitized to analysis and theorization in such context. Second, the sociotechnical perspective is foundational to the study of information systems (Sarker et al., 2019), which connects my work to past IS research and contributes to building cumulative tradition within the field. Finally, the sociotechnical nature of changes and the need for considering the related dimensions has been recognized and embraced by scholars engaged in early research of ML in organizations (Asatiani et al., 2021; Berente et al., 2021; Grønsund & Aanestad, 2020; Lytinen et al., 2020). This allows for the positioning of my work in the existing body of knowledge and the identification of opportunities for advancing that knowledge. I provide an overview of the background literature and position the three essays included in this thesis in the following section.
2. **ML in organizations: the rise of ML use and open challenges**

In this section, I situate the thesis within the research on ML in organizations and connect my work to related practical challenges faced by organizations. I first discuss the rise of ML, where I explicate the key differences between ML systems and traditional IT systems, as well as provide an overview of business opportunities that were unlocked through the organizational adoption of ML. Next, I provide an overview of organizational challenges within the use of ML and specifically expand the theoretical grounding of those challenges which are addressed by the essays included in the thesis. This section, thus, complements the background synopsis from the introductory section and performs a “landscape building” work, which constructs an intertextual field (Locke & Golden-Biddle, 1997) within which my work is located.

### 2.1 The rise of ML

We have seen tremendous growth in ML experimentation and use by organizations in recent years – a McKinsey survey reports that the share of survey respondents (representing the full range of regions, industries, company sizes, functional specializations, and tenures) who say that their organization have adopted AI in at least one function grew from 20% in 2017 to 50% in 2022 (Maslej et al., 2023, p. 198). This phenomenon is worthy of being a central topic for research not merely because of its novelty and widespread presence in businesses and other organizations. Indeed, ML use represents a significant departure from the familiar area of digital technology use in organizations because ML systems learn from data rather than being explicitly programmed (Brynjolfsson & Mitchell, 2017), which results in learning, higher degrees of agency, and inscrutability (Berente et al., 2021). Therefore, I discuss next the characteristics of ML systems which make them a distinctive and novel form of IT systems. To complement the picture and motivate the importance of ML technologies to organizations, I also provide a brief overview of the business opportunities created by ML systems.

#### 2.1.1 ML versus traditional IT systems

Learning prominently features in the name of ML technology. And it is learning that clearly distinguishes ML from traditional IT systems. Learning in ML stands for the process involved in the creation of these systems (Brynjolfsson & Mitchell, 2017). For this thesis, it is important to recognize more explicitly where the differences and similarities between ML and traditional IT systems lay. Explaining this technical detail allows one to understand why ML systems can perform tasks that would otherwise be too costly for human programmers to code or even outright too complex and impossible to do so. At the same time, this understanding informs deeper insight into the organizational use of ML, which I further explore and develop throughout this thesis.

Let us note that any useful digital system must undergo at least once through the following two phases – development and operation (Lyytinen & Newman, 2008; Volkoff et al., 2007).
Iterations between these phases are possible and, in many cases, desired or even necessary (Lyytinen & Newman, 2008; Paterson et al., 2021). Irrespective of the number of iterations, both traditional IT and ML systems meaningfully resemble each other in the latter operational phase.

![Digital System in Operation](image)

**Figure 1.** A simplified representation of a digital system in an operational phase.

We can schematically represent any digital system as a “box” processing inputs and converting them into outputs using an inferential logic or system frame that was encoded into it during the development phase (Dennett, 1984; McCarthy, 1981) (Figure 1). For example, an enterprise resource planning system (a traditional IT system) might take the current inventory level as data input and generate a re-stocking purchase order based on a set of decision rules encoded by system developers. In another example, an ML system for face recognition might take an image file in JPEG format as input and generate the name of a person that is on the picture as output based on an artificial neural network created during the system training. Given this simplified representation, ML systems can integrate with other types of digital systems by partaking in the input/output transformation chains and, thus, can play a variety of potential roles. This resemblance is essential for the valuable contribution of ML systems to the economy because it allows ML systems to substitute for existing traditional IT systems or integrate with them.

![Traditional IT System Development vs. ML System Development](image)

**Figure 2.** Difference between traditional IT system development (left) and ML system development (right).

In the development phase, however, there is a crucial difference between traditional IT and ML systems. That difference originates from dissimilar ways in which the inferential logic is encoded into these systems. The development of traditional IT systems involves the process of crystallizing the domain knowledge in ways that absorb, reduce, and explicitly codify it into machine-executable instructions (Kudaravalli et al., 2017). Thus, in traditional IT system development (Figure 2. left) developers control “what” the system does through explicitly codifying and changing the inferential logic encoded into the system. Hence, software developers first learn by themselves and then translate their knowledge and understanding into digitally encoded algorithms (Eischen, 2002, p. 39).
The development of ML systems (Figure 2. right), however, externalizes a meaningful share of learning from the system developers and instead places it onto ML models. These models learn through a training procedure resembling trial and error – multiple potential inferential logics of the system are compared against each other utilizing a training data set and a loss function, which measures the training error (Paterson et al., 2021). In this approach, ML system developers do not explicitly encode the final inferential logic of the system. Instead, they control it only indirectly through the provision of the training data, loss function, and selection of model type, its architecture, and hyperparameters defining model characteristics and the training procedure (Paterson et al., 2021). Hence, unlike in traditional IT systems, ML system developers provide less domain understanding directly, but they rely primarily on the training data to shape the inferential logic of the system (Kambhampati, 2021). In other words, ML system developers control only “how” the system learns through participating in data management and designing model learning, thus they implicitly shape the ML system frame. Therefore, due to the iterative nature of ML system development and use (Paterson et al., 2021), these systems retain significant differences from traditional IT systems throughout their lifetime, including operation, if they continue to be retrained.

2.1.2  Business opportunities created by ML

The possibility of utilizing data to train machines means that organizations can now overcome some of the obstacles that have been limiting computerization and digitalization for decades (Brynjolfsson & Mitchell, 2017). These limitations previously originated from the software developers’ ability to understand and codify their knowledge (Autor, 2014, p. 8):

“Engineers cannot program a computer to simulate a process that they (or the scientific community at large) do not explicitly understand. This constraint is more binding than one might initially surmise because there are many tasks that we understand tacitly and accomplish effortlessly for which we do not know the explicit “rules” or procedures.”

The consequences of ML systems not requiring explicit programming, but rather provision of suitable training data and procedures, are tremendous – organizations can now introduce digital technology into multiple areas where it was previously impossible or economically unfeasible. For example, the successful execution of a variety of tasks in organizations relies on the ability to comprehend text, and speech, or identify objects using vision. These tasks represent notorious challenges for traditional IT systems because of the limited ability of software developers to explicitly codify instructions for how to execute these tasks. Recent advances in ML, however, have proven that it is possible to achieve high performance on these tasks – according to several recognized benchmarks ML algorithms might perform as well as or even better than humans. Figure 3 illustrates improvements in the ML performance on a variety of such tasks.

Thus, organizations can now use ML to execute these types of tasks. Similar performance improvements have been achieved for other types of tasks, thus unlocking commercial use of ML for classifying inputs, predicting numerical values, ranking items, identifying complex association patterns, grouping similar examples, and generating images or text, which all represent a form of a prediction task (Agrawal et al., 2022). Triggered by these diverse capacities of ML technology, businesses and other organizations are starting to adopt ML into their daily operations. Evidence of experimentation with and deployment of ML comes from a variety of contexts and industries, including investing (Ge et al., 2021; Sturm, Koppe, et al., 2021), predictive policing (Waardenburg et al., 2022), patient treatment in hospitals (Lebovitz et al., 2021), recruitment (Trocin et al., 2021; van den Broek et al., 2021), consumer lending (Strich et al., 2021), analyzing routes of cargo ships (Grønsund & Aanestad, 2020), creative design consulting (Trocin et al., 2023), and fraud detection (Asatiani et al., 2021; Kim et al., 2022). Furthermore, different implementations of ML can be found across the full length of the value chain, for internal use within an organization, as well as when facing external stakeholders (e.g., customers or suppliers) (Bughin et al., 2017). This vast potential makes ML potentially a transformative technology for organizations globally (Brynjolfsson & Mitchell, 2017).
2.2 Challenges of ML

In tandem with immense opportunities brought by ML diffusion, organizations also face significant challenges when taking these technologies into use and later during their operational life. This thesis focuses on three of these challenges. The first one centers on the overall understanding of how ML technologies have been diffusing into commercial use. Particularly at the time when this research work was starting, there was a lot of publicity and hype around ML technology implementations by forerunners. However, simultaneously there was a scarcity of research on the overall diffusion of the technology into commercial use. On the practical side, this resulted in significant uncertainty for many organizations in their technology management and strategy development activities. It also revealed weaknesses in the current research methodologies for technology diffusion monitoring.

The second organizational challenge of ML, which I address, is the limited understanding of how organizations successfully develop ML-based capabilities. Despite knowing that organizational capability development and use is a process that unfolds over time and involves iterations and accumulation of experience, a more nuanced understanding of this critical process – an understanding which considers novel and unique characteristics of ML technology – has been missing (Mikalef et al., 2023; Mikalef & Gupta, 2021). Overall, the research on MLbC is still in its infancy. This is surprising, given the vital role of capabilities in determining organizational performance and competitiveness.

Finally, the third challenge motivating this thesis is the adaptation of MLbC to new operating environments or application domains. ML systems are limited by the classical “frame problem” in AI – when they encounter new or distinct types of situations compared to those for which they were initially designed and trained, they cannot independently reflect on their subpar abilities and readjust their inferential logic (Grønsund & Aanestad, 2020). Instead, they need new training data, which is generated within or through an organizational sociotechnical system. This challenge has not been meaningfully addressed, despite recognizing it as a problem.
and the fact that organizations constantly face changes. Overall, conducting research motivated by these three challenges aims at addressing gaps in our knowledge that both advance scholarly conversation and bear practical relevance.

2.2.1 The broad range of challenges related to ML

Before discussing the three challenges of ML addressed by this thesis it is still important to recognize that we are far from understanding and sufficiently addressing many other challenges related to ML and organizations. While discussing these other challenges in detail goes beyond the scope of my present work, it is prudent, informative, and sobering to at least mention some of those open challenges. For example, they might relate to the ability of organizations to keep up with the rapid rate of technology advancements (Ransbotham et al., 2018) or the capacity to meet inconsistent regulatory requirements across different countries or regions (EU Parliament, 2023; Scherer, 2015).

Importantly, ML adoption by organizations might also generate new or reinforce existing negative consequences of digital technology. The potential for reinforcing unfairness is the first one – ML models may produce unfair or discriminatory outcomes for certain groups of people, especially those who are underrepresented or marginalized in the training data or the society (Teodorescu et al., 2021). ML models may also inherit or amplify human biases that are present in the training data (Maslej et al., 2023, Chapter 3). For example, a natural language processing system may use gender stereotypes to generate text, or a recommender system may reinforce existing preferences or opinions of the users. These biases may affect the quality or validity of the ML outputs, as well as limit the diversity or creativity of the solutions (Balasubramanian et al., 2022).

The next challenge is privacy (Lwakatere, Raj, et al., 2020). ML models may collect, store, process, or share sensitive or personal information of the individuals or groups represented in the training data. A healthcare system may, for example, reveal the medical records of patients, or a social media platform may expose the behavioral patterns of users. These actions may infringe the privacy rights of individuals and expose them to potential harm or abuses. This challenge relates to the lack of or limited transparency, explainability, or reliability of ML models in their functioning and generation of outputs (Berente et al., 2021). For instance, it might not be possible to explain why a self-driving car made a certain move, or why a stock trading system executed a certain transaction. These limitations may reduce the confidence or satisfaction of the ML system users and other stakeholders, not to mention increasing the uncertainty in decision-making.

Another challenge is the environmental footprint. ML models may consume enormous amounts of energy in their development, deployment, or maintenance (Schwartz et al., 2020). For example, a neural network system may require massive computing power and data storage to train and run its complex algorithms and, thus, might generate a significant carbon footprint. These impacts, if realized, would lead to organizations harming the environment, climate, and sustainability efforts (Mucha et al., 2022a).

Last, but not least, organizational use of ML might have negative implications on employees. They might develop learned helplessness as ML models in some situations reduce the autonomy, agency, or responsibility of the human actors who interact with them (Balasubramanian et al., 2022). Such changes might also undermine the professional role identity of employees, since ML models may challenge the expertise, authority, or legitimacy of human professionals (Strich et al., 2021). Job displacement is another possible consequence of the increased use of ML (Brynjolfsson & Mitchell, 2017). ML systems may replace human workers in performing tasks that are routine, repetitive, or low skill. These outcomes may diminish human skills, values, or identities. Overall, these challenges are not mutually exclusive and the list I provided here is not exhaustive. They may interact or overlap with each other, creating complex problems that require both further research and awareness coupled with proactive measures in organizations employing ML technologies. Overall, research on ML in organizations presents many opportunities for contributing to theory and practice.
2.2.2 Challenges with monitoring ML technology diffusion into commercial use by organizations

Most of the research concerned with monitoring the growth and diffusion of ML technologies has concentrated on the pre-commercial stage of the technology lifecycle. Studies on the commercial diffusion of ML have been primarily conducted by practitioners and only a limited number of academics. Next, I provide an overview of these studies and their key selected findings. Finally, I identify methodology development as an area for advancing current research on commercial technology diffusion monitoring in general and ML in particular.

Monitoring pre-commercial diffusion of ML primarily leverages documents, which are widely available and accessible – scientific publications and patents (Bianchini et al., 2022; Fredström et al., 2021; Liu et al., 2021; Toole et al., 2020). Yet, businesses need to monitor technology diffusion in the later stages of the technology life cycle as well because commercialization is not guaranteed even if inventions are backed by research and patents (Grant, 2016, p. 243). To add to this, even technologies which do enter commercialization must face a variety of adoption challenges (Ropers, 2010), which might take a lot of time (Roper et al., 2011, sec. 1.2).

Academic research on the commercialization of ML technologies with a particular focus on monitoring of their diffusion has not gained prominence even though studying ML in an organizational context is widespread. Only a limited number of papers address, at least partially, the very issue of commercial diffusion of that technology. These studies typically refer to a broad portfolio of technologies labelled as AI and point to the growing importance of ML technologies to businesses and other organizations. For instance, a study by Lyu & Liu (2021) found that AI was the dominant technology mentioned among keywords related to technologies in job postings from energy firms during 2010-2019. Depending on the year, AI appeared in 4%–8% of the content of job postings. Content from public sources generated by ten leading retail companies globally and the press was analyzed by Weber & Schütte (2019) to investigate the AI adoption of these companies. They reported that eight of the ten companies utilized AI, but there were significant variations in the degree of AI incorporation into their daily business operations. In addition, an annual AI Index Report (Zhang, Mishra, et al., 2021, p. 106) gives the count of “AI” and “machine learning” keyword mentions in corporate earnings calls over time and underscores the importance of this technology to key business decision-makers. Furthermore, specific challenges, benefits, or other aspects of ML adoption in organizations are uncovered by multiple qualitative case studies (e.g. Asatiani et al., 2021; Grønsund & Aanestad, 2020; Ruissalo et al., 2022; Strich et al., 2021; Trocin et al., 2023; van den Broek et al., 2021), but the issue of monitoring the commercial diffusion of ML is not within the scope of these studies. However, only a small portion of all studies on commercial diffusion of ML technologies come from academic research.

Monitoring the commercial diffusion of ML technologies has been an active area of research interest of national statistical offices and other non-profit or governmental organizations. The potentially high impact of ML on the economy (Ransbotham et al., 2020; Montagnier & Ek, 2021), though some cases employ patent analysis (Toole et al., 2020) and keyword-based website content analysis (Mattila et al., 2017). These studies reveal a low level of ML adoption (Eurostat, 2020; Montagnier & Ek, 2021; Zolas et al., 2020, p. 12), except for large organizations in highly developed countries (Eurostat, 2020; Montagnier & Ek, 2021; Zolas et al., 2020, p. 12).

Reports on the state of commercial diffusion of ML have been published most actively by management consulting firms and other commercially oriented organizations. Compared to the results from academic publications or national statistical offices, these reports are more up-to-date, due to their publication frequency and high number of such reports. They reveal that from 2017 to 2020, the level of ML adoption rose steadily, with commercial adoption of ML reaching 50%–60% of survey respondents or companies surveyed (Balakrishnan et al., 2020; Bughin et al., 2017; Cam et al., 2019; Chui & Malhotra, 2018; Lorica & Loukides, 2018; Lorica & Nathan, 2019; Magoulas & Swoyer, 2020; Ransbotham et al., 2017, 2018, 2019, 2020). Nevertheless, these reports need careful consideration of the results and their validity, as they are less transparent in terms of methods and might be biased due to conflicts between...
business interests and the subject of the study. Notwithstanding limitations, these reports provide a rich set of information.

The diffusion of ML technology into commercial use by organizations is only partially understood by current research and practitioner studies. One reason for this shortcoming is the use of methods that limit what and how can be studied. Several limitations affect the survey methods used by national statistical offices and consulting firms. One of them is the provision of a “snapshot-in-time” perspective instead of a “moving pictures” perspective (Rogers, 2010, pp. 126–130). This is a disadvantage, especially for diffusion processes that advance rapidly, such as ML technology. Running surveys at multiple points in time to remedy this poses new challenges – the respondents’ perception of innovation is distorted (Rogers, 1983, p. 117) and non-response bias is worsened (Roper et al., 2011, p. 103). Moreover, technology monitoring using survey research can face long time lags, difficulties with definitions of technical terminology, and in the case of studies run commercially, low transparency, replicability, and impartiality regarding specific methods and sampling approaches, which were all identified as potential issues in ML diffusion studies by consulting firms (Montagner & Ek, 2021). Therefore, survey-based methods are not enough for monitoring the commercial diffusion of technology. Studies relying on content analysis present a viable alternative or a source of complementary research to survey-based studies. Research relying on content analysis, however, utilizes thus far only relatively crude measures of technology diffusion based on simple keyword counts in job postings, corporate websites, or investor earnings call transcripts (Goldfarb et al., 2023; Lyu & Liu, 2021; Mattila et al., 2017; Zhang, Mishra, et al., 2021). Thus, these studies do not consider the complexity of the organizational processes involved in technology adoption, their multi-phase nature (Cooper & Zmud, 1990), and overlook many mundane challenges standing in the way between experimentation and commercial application of ML in daily business practices (Trocin et al., 2023). These challenges motivate my research presented in Essay 1 of this thesis.

Table 2. Summary of the motivation underlying the research questions of Essay 1.

<table>
<thead>
<tr>
<th>Research questions</th>
<th>Theoretical grounding and contribution opportunity</th>
</tr>
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<tbody>
<tr>
<td>RQ1.1: How to extend content analysis methods for technology diffusion monitoring to account for multiple phases in the adoption of technologies into commercial use by organizations?</td>
<td>Technology monitoring is fundamental to R&amp;D planning, technology management, and strategic decision-making. Approaches to monitoring technology diffusion at precommercial stages of the technology lifecycle have advanced rapidly, particularly in the area of patent analysis. However, these methods do not address monitoring of commercial stage diffusion. Methods used at that later stage have been primarily limited to point-in-time surveys and keyword-based content analysis. The former approach provides only a snapshot view and is often limited by low transparency, replicability, and sample selection bias, not to mention potential conflicts of interest when surveys are conducted by commercially driven entities, such as consulting firms. Monitoring commercial diffusion of technology using content analysis has been limited to crude measures utilizing keyword counts and does not reflect the multiphase and complex process of organizational adoption of complex digital technologies. Particularly in the context of commercial diffusion of ML into organizational use, most information comes from consulting firms and other commercially driven entities.</td>
</tr>
<tr>
<td>RQ1.2: How have machine learning-based technologies diffused across different organizations?</td>
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2.2.3 Challenges with the development of ML-based organizational capabilities

Literature concerned with ML-based capabilities in organizations can be divided into two perspectives – (1) organizational use of ML, which is rooted in organizational sciences and IS research and (2) machine learning operations (MLOps) research originating from the computer science field. Before discussing these two emerging perspectives, I anchor my problematization in the background research on where organizational capabilities come from and how they are developed and maintained in organizations. Given this background, I identify that
studying MLbC development requires recognizing (1) its processual nature – the unfolding of the process over time and other temporal aspects, (2) the need for achieving and maintaining alignment within that process, and (3) appreciating the importance of context within which capabilities are developed and utilized (Figure 4). This is grounded in the notion that capabilities are information-based and “are developed over time through complex interactions” (Amit & Schoemaker, 1993, p. 35), which makes MLbC a novel problem for practitioners and scholars due to differences in how traditional IT and ML systems are developed.

**Organizational Capability Development Process**

![Organizational Capability Development Process Diagram](image)

Figure 4. Studying organizational capability development calls for recognizing its (1) processual/temporal nature, (2) the need for aligning resources, and (3) context sensitivity.

The ability of an organization to align the deployment of internal resources and competencies to achieve optimal results is what the resource-based view (RBV) (Barney, 1991; Wernerfelt, 1984) and resource orchestration (RO) (Sirmon et al., 2007, 2011) literature refer to as organizational capabilities (Amit & Schoemaker, 1993; Bharadwaj, 2000). As they are not easily purchased, organizational capabilities are often developed internally in alignment with organizational goals (Sirmon et al., 2007). Capability is not just a one-off effort to perform a task or set of tasks in an organization – activities involved in a capability must be dependable and achieve a certain level of routinization (Helfat & Peteraf, 2003). To achieve this, alignment between the key resources—people, processes, and technology (Amit & Schoemaker, 1993; Helfat & Peteraf, 2003)—is required. Alignment in this context implies “both doing the right things (effectiveness), and doing things right (efficiency)” (Luftman et al., 1999, p. 4). A desirable level of alignment can only be achieved over time with proper coordination and integration (Bharadwaj, 2000; Sirmon et al., 2007). Furthermore, as IT-business alignment literature highlights, capability development relies on “coordinating activities across IT and non-IT domains within the firm” (Luftman et al., 2017, p. 27). In this sense, therefore, IT-business alignment research is consistent with RBV and RO literature.

Developing capabilities is a process that is iterative, multi-level, and sensitive to context. It involves unclear feedback, exploration of alternatives, and several cycles of experimentation (Helfat & Peteraf, 2003). Therefore, the temporal aspect is key to describing the processes that underlie capability development. In addition, capabilities exist at various levels within an organization (Sirmon et al., 2011), and specialized capabilities at higher levels are formed by lower-level capabilities (Grant, 2016). This means that the alignment of the efforts to develop capabilities at various levels within an organization should be considered in the governance and process of capability development (Grant, 2016). Also, capabilities are not only technological functions or individual skills, but they require the alignment of various resources, including human, intangible, and tangible resources (Bharadwaj, 2000; Grant, 2016). Thus, we must recognize the contribution of structures and individuals in developing capabilities and the coordination necessary to align their outputs. Lastly, the development of capabilities is guided and constrained by the context, both external and internal (Gavetti, 2005; Sirmon et al., 2007).
A dynamic response to the challenges and opportunities from the environment is needed to maintain the alignment of the components of a capability during its development. Hence, the alignment of the process of capability development and the environment relies on the constant adaptation and monitoring of environmental changes (Sirmon et al., 2007; Wilden et al., 2016).

Overall, based on the review of this background literature I recognize the importance of temporal aspects, alignment, and context in understanding organizational capabilities. With these three key topics in mind, I cover next the research on MLbC that originates from studies focusing on MLOps, as well as the organizational use of ML.

Some of the aspects related to MLbC are addressed by research within computer science that focuses on MLOps. MLOps represents practices which tackle the specific challenges of not only implementing ML technologies but also serving them in production. “These challenges include aspects such as model construction, training, and monitoring, as well as high requirements for data workflows, such as data cleaning, analysis, validation, and feature extraction” (Mucha et al., 2023, p. 172). Therefore, MLOps requires a novel approach to enable optimal performance and reliability (Amershi et al., 2019; Mäkinen et al., 2021; Renggli et al., 2021; Zhou et al., 2020). However, the MLOps research concentrates on technical aspects, thus, simplifying the problem of MLOps’ sensitivity to external context and viewing it primarily through data. Such a perspective treats the organizational dimension of MLbC development as secondary.

Table 3. Summary of the motivation underlying the research questions of Essay 2.

<table>
<thead>
<tr>
<th>Research question</th>
<th>RQ2: What mechanisms facilitate the development of machine learning-based capabilities?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Theoretical grounding and contribution opportunity</td>
<td>Organizational capabilities are one of the key determinants of the performance and competitiveness of organizations. Capabilities are developed iteratively and over time, where multiple resources need to be coordinated and aligned. ML technology presents a significant potential for organizations to create new MLbC, but also is challenging due to the unique nature of ML technology. Nascent research on MLOps provides important insights into the technical aspects of ML technology development, release, and operation. However, by viewing MLbC primarily through technical and data aspects, this perspective abstracts away the organizational context within which ML technology is developed and thus overlooks the influence of external context on this process. Early research on the organizational use of ML falls short in considering the temporality of MLbC development as an alignment process occurring throughout the phases of development, release, and operation. While we know what types of resources are needed to develop MLbC, we still do not know how this is done. The focus of empirical studies has been on the initial stages of development (development and release) and, thus, a more holistic understanding of the MLbC development process is absent. This is particularly problematic, because the iterative nature of MLbC development, which highlights the need to consider temporality, alignment of multiple resources, and sensitivity to context.</td>
</tr>
<tr>
<td>Practical relevance</td>
<td>Despite the relative ease of piloting ML projects in organizations, scaling and deploying them has proven to be challenging. Only one in 10 companies running ML initiatives realize satisfactory outcomes. This mismatch between the newly unlocked raw technical capabilities of ML and its productive harnessing highlights the difficulty of creating ML-based capabilities in organizations.</td>
</tr>
</tbody>
</table>

Research in IS and organizational sciences has identified key resources required for the creation of MLbC, but the theorization of how such resources can be combined and developed into MLbC is still lacking (Mikalef & Gupta, 2021). Thus, the process view of MLbC development and its iterations and extension throughout the entire lifetime of MLbC remains a black box. The current literature is insufficient in addressing the temporality of MLbC development, which is an alignment process that spans the phases of development, release, and operation (Gronlund & Annestad, 2020; Mikalef & Gupta, 2021; Strich et al., 2021; van den Broek et al., 2019). In addition, the operation of ML-based solutions demands organizational commitment from multiple levels and functions (Raisch & Krakowski, 2021), which is often ignored by focusing on a single level of analysis. Also, the development of MLbC depends on the organizational context because the outcome of MLOps can drastically alter how the users and other organizational actors execute different tasks and how the organization accomplishes its operational goals within its structure (Asatiani et al., 2021). These limitations imply that we lack an overarching framework that can systematically account for the technical, organizational, behavioral, and temporal aspects of ML-based capabilities.
In summary, past research on organizational capabilities highlights the importance of understanding the process of capability development, due to the vital role of capabilities in determining organizational performance and competitiveness. Despite recognizing ML as a novel technology with unique characteristics when compared to traditional IT systems and significant potential for contributing to the creation and development of organizational capabilities, we still have only a rudimentary understanding of MLbC. We need to understand the process and underlying mechanisms of MLbC development. Motivated by these challenges, I conduct research presented in Essay 2.

2.2.4 Challenges with ML systems facing novel operating environments or application domains

Research on how digital systems can function despite changes in the operating environment or application domain originates from early AI research. This challenge has been called “the frame problem” and it points to the fundamental role of people who encode an a priori inferential logic into a digital system. If changes in an operating environment or application domain result in a setting that the system is not prepared for – falls outside of the a priori frame of the system – then there is a need for human intervention to encode new or updated inferential logic into that system. In this thesis, I refer to the organizational process of changing the inferential logic encoded into a digital system so that it functions in a novel operating environment or application domain as reframing. Next, I provide an overview of traditional IT system reframing, and then turn attention to ML systems. The process of ML system reframing is novel and different because it relies primarily on data and not on explicit changes in the encoded inferential logic. Therefore, I also discuss research on organizational data work, which allows me to point out a gap in our understanding. Namely, we still do not understand how organizations reframe operational ML systems through data work.

Prior IS research offers several insights into traditional IT system reframing. For such systems, the reframing rests on the software developers’ ability to crystalize domain knowledge in ways that absorb, reduce, and codify it into machine-executable instructions (Kudaravalli et al., 2017). It involves making explicit choices between multiple competing alternatives for implementing specific functionality and related inferences (Volkoff et al., 2007). Particularly when the operating environment changes frequently, updating the rules governing the system’s functioning requires specialized and multi-layered organizational structures, where some team members start proactively anticipating the need for changes while others reactively respond to identified failures (Salovaara et al., 2019). Irrespective of the adopted organizational approach to reframing traditional IT systems, this process critically depends on software developers’ ability to adjust their cognitive frames and translate them into system frames by appropriately encoding the new understanding into digital form (Recker & Green, 2019).

Reframing of ML systems, however, differs from traditional IT reframing because it does not solely depend on how well developers can translate their shifting cognitive frames to digital form (Balasubramanian et al., 2022). Instead, generating, finding, selecting, and adjusting training data to reframe the ML system takes the front stage, thus calling organizations to radically develop and readjust the surrounding data work (Strickland, 2022). "Data work" and "data practices" have emerged as salient topics in information systems (IS) and organizational literature. Data work has been defined as “turning data into action” (Foster et al., 2018, p. 1414) or “human activity related to creating, collecting, managing, curating, analyzing, interpreting, and communicating data” (Bossen et al., 2019, p. 466). In this thesis, organizational data work stands for the actions and organizational practices that shape, intentionally or unintentionally, the data used in ML systems.

While data in organizational settings is often seen as ‘given’ objective ‘datum,’ organizational scholars have started to highlight data as socially contingent and constructed where data and its quality are tied with “contingent and contested social practices” (Aaltonen et al., 2021; Ilidadis & Russo, 2016; Muller et al., 2019) which are nonneutral (Alaimo & Kallinikos, 2022). Data are not “a sort of natural or foundational substance” (Aaltonen & Penttinen, 2021, p. 5924), but rather discovered, curated, and prepared through specific practices (Lebovitz et al., 2021; Mikalsen & Monteiro, 2021; Parmiggiani et al., 2022). Thus, it is organizational actors and their understanding that guide when, how, and what data to collect, as well as what it
means to clean and process data and according to what criteria. Inherently, data is messy and is never “raw,” but rather always “cooked” (Mikalsen & Monteiro, 2021; Parmiggiani et al., 2022) in some form by previous interpretations, decisions, and actions (Gitelman, 2013, p. 3).

Despite the criticality of data work to ML system development, research focusing on ML in organizations is only scratching the surface of the reframing problem. For continually learning ML systems, data work permeates both system development and use (Asatiani et al., 2021; Gronlund & Aanesstad, 2020), thus creating multifaceted and complex mutual relationships and feedback loops (Mikalsen & Monteiro, 2021; Raisch & Krakowski, 2021) where social construction of data through data work plays a vital role. Already at the initial phases the system design determines the boundaries of what the system can do and how. These decisions are not value-neutral because they reflect either explicit or implicit preferences of system developers (Faraj et al., 2018). Iterative development of the system and the constant need to explicate system objectives leads to multiple discretionary and subjective design choices that must be negotiated between different system stakeholders (Passi & Sengers, 2020; van den Broek et al., 2021; Waardenburg et al., 2022). Similarly, the selection of the training data frequently excludes some part of knowledge – for example, ML systems used in a medical context might reflect know-what aspects of medical knowledge, but lack data representing practical knowledge, which can yield disappointing performance of ML systems in practice despite seemingly superior accuracy of predictions they deliver (Lebovitz et al., 2021).

However, the connection between the organizational processes shaping the training data – organizational data work – and the process of changing the inferential logic encoded into an operational ML system – ML system reframing – in response to the changing operational environment or application domain has not been sufficiently explored. Thus far, scholars have taken three approaches to ML system reframing – (1) oversimplifying, not recognizing, or keeping it outside of the research scope, (2) recognizing it only implicitly or (3) explicitly, but not providing insights on the process itself. Many studies do not address reframing, as they only cover the initial stages of ML system development (Faraj et al., 2018; Gronlund & Aanesstad, 2020; Passi & Sengers, 2020; Ruissalo et al., 2022; van den Broek et al., 2019) or other aspects (Ge et al., 2021; Lebovitz et al., 2021; Strich et al., 2021; Waardenburg et al., 2022). Some papers imply that ML systems require reframing, but without going into details about how this is done (Bair & Maruping, 2021; Lyytinen et al., 2020; Mucha et al., 2023; Raisch & Krakowski, 2021; Shollo et al., 2022; Teodosescu et al., 2021). Only a handful of studies explicitly recognize the significance of ML system reframing, but they do not explain the underlying sociotechnical process of data work it entails (Berente et al., 2021; Sturm, Koppe, et al., 2021). Thus, we still need to learn more about how organizational data work gives rise to the reframing of ML systems, especially those that face changing data distributions and high risks or costs of errors.

This topic is an important research problem and is also a major challenge for organizations because organizations create value with ML systems mostly over time, and not during the development or initial implementation only (Shollo et al., 2022). Since the operating environment rarely stays constant and organizations need to modify, develop, and combine their resources to keep their capabilities based on ML valuable (Sirmon et al., 2007), ML systems inevitably need to be reframed.

Table 4. Summary of the motivation underlying the research question of Essay 3.

<table>
<thead>
<tr>
<th>Research question</th>
<th>RQ3: How do organizations reframe their operational ML systems through data work to retain ML system performance?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Theoretical grounding and contribution opportunity</td>
<td>Reframing information systems has been recognized as a long-standing challenge. Such systems cannot operate and perform well in contexts which require inferential logic that is different from the one that was previously encoded into the system. Reframing traditional IT systems requires making explicit changes in the software code. These changes are an outcome of a process involving the crystallization of domain knowledge in ways that absorb, reduce, translate, and codify it into machine-executable instructions. This approach, however, is not suitable for ML systems because these systems learn from training data and not through changes in the code. Emerging research on organizational data work highlights the complex, contested, and equivocal nature of organizational processes for generating data. Data does not exist in a raw form that simply needs to be discovered – instead, the generation of data requires interpretative acts, negotiations between various groups or priorities, and balancing of multiple, sometimes contradictory, preferences. While the sociotechnical nature of data work has been recognized, we...</td>
</tr>
</tbody>
</table>
do not know how such work shapes ML systems, which face changes in the operational context or application domain. In particular, past research has taken three approaches to reframing ML systems: (1) Oversimplifying, not recognizing, or keeping ML system reframing outside of the research scope; (2) Recognizing some aspects of ML system inferential logic change, but not problematizing it as system reframing or revealing the underlying sociotechnical processes; (3) Explicitly referring to the ‘frame problem,’ but not explaining the underlying sociotechnical process of data work in operational ML systems. Thus, overall, research recognizes the challenging nature of organizational data work, but fails to explore how that work manifests itself in organizations reframing their operational ML systems exposed to changes in input data distributions.

Practical relevance

Very few organizations or processes within organizations can operate without experiencing changes. Such changes can originate from the external operational environment or be initiated internally with the intention of, for example, expanding business, improving efficiency, or reducing risk. Since ML systems are increasingly used across different processes and tasks in organizations, they too need to be adapted to changes. Therefore, reframing ML systems is an important process for an increasing number of organizations.

In sum, I have shown that ML system reframing directs our attention to both technical and organizational aspects of data work, which play a vital role in arriving at an adequate reframing approach. This approach is necessary for organizations that use ML systems to tackle tasks that might be exposed to changing operating environments or application domains, thus facing changing input data distributions. While the nascent research on ML system use in organizations has shown the salience of reframing and addresses multiple aspects that affect the process and its outcomes, we still do not know how organizations effectively engage in data work underlying reframing tasks. This is surprising given that overwhelming evidence shows that changes in input data are likely to happen eventually during the operational use of most ML systems (Brzezinski & Stefanowski, 2013; Kim et al., 2022; Sturm, Koppe, et al., 2021). Therefore, one critical element in improving the organizational use of ML systems is to understand better how to organize for and enable reframing for adequate performance while the system faces constant and occasionally drastic changes in its input data distributions. Motivated by this challenge, I conducted a study presented in Essay 3.
3. Essays

In this section, I provide an overview of the essays’ methods, data, and key findings, as well as summarize the key contributions of each essay and how they address the selected research questions. With these three essays, I analyze how ML technologies have been spreading into organizational use and how certain processes within organizations need to be shaped to successfully leverage ML in business. Essay 1 scopes out the status of ML technology commercial diffusion across time, industrial sectors, and digital intensities of firms. Next, to provide a more in-depth understanding of the mechanisms inhibiting and promoting the successful development of organizational capabilities based on ML technologies, Essay 2 analyses multiple organizations engaged in such work. Essay 3 focuses on one of the key structural characteristics inhibiting the alignment of ML-based capabilities identified in Essay 2 – that is context sensitivity of MLbC. Thus, Essay 3 uncovers the organizational processes required for ML systems to function in novel operating environments or application domains.

3.1 Essay 1. AI diffusion monitoring among S&P500 companies: Empirical results and methodological advancements

The purpose of this essay was twofold. First, it was to develop a content analysis method for monitoring the diffusion of technologies at the commercial stage of lifecycle, while accounting for the multiphase nature of organizational adoption of complex digital technologies. The second objective was to use that method to map out and validate the status of machine learning-based technologies’ diffusion into commercial use among large firms. Thus, this essay consists of the method development part and that of empirical exploratory analysis, based on the newly proposed method.

3.1.1 Overview of data and method

When developing the proposed method, we drew on the existing approaches for technology diffusion monitoring which utilize content analysis (Lyu & Liu, 2021; Mikova & Sokolova, 2019; Porter & Cunningham, 2004, secs. 6–8; Roper et al., 2011, sec. 5.2; Segev et al., 2015; Teece, 1980; Zhang, Mishra, et al., 2021, p. 106). However, to extend this approach, we enriched it by incorporating insights from research on the diffusion of innovations (Rogers, 2010) and particularly the adoption of complex digital technologies in organizations (Cooper & Zmud, 1990; Meyer & Goes, 1988; Toledo, 2005). Thus, our proposed method involved not only the identification of relevant keywords in the content selected for analysis but also the classification of each coding unit that is the “unit of text to be classified” (R. P. Weber, 1990, p. 22) into phases of technology adoption by organizations. Figure 5 provides an overview of the steps involved in the proposed method.
We applied the proposed method in the exploratory analysis of ML technology diffusion into commercial use by large firms. In the first step - scoping and situating the technology diffusion monitoring project – we selected “artificial intelligence” and “machine learning” as the main keywords in the analysis. We also conducted a review of previous studies concerned with the diffusion of ML into commercial use by organizations. These studies included academic sources, as well as those produced by, for example, national statistical offices and consulting firm reports. The next step - sampling and content retrieval – involved narrowing down the focus to S&P 500 companies, as a study sample, and defining the period for the study, which was set from January 2004 to May 2019. We, furthermore, retrieved 2,047 investor event transcripts of S&P 500 company executive presentations from the Thomson Reuters Eikon.
database for analysis in the next step. In the third step - analyzing and classifying content – we iteratively developed the coding scheme, which contained three codes: mentioning AI, piloting AI, and commercial use of AI (see Table 7 for code definitions and exemplary quotes). Next, we applied that coding scheme to produce input for the ultimate step - presenting, exploring, and exploiting the results.

### 3.1.2 Overview of empirical exploratory analysis and findings

The findings from our exploratory analysis allowed us to draw insights into the commercial diffusion of ML technologies among S&P500 companies. By aggregating the results of document-level coding into a table we could trace over time the phases of ML adoption by individual companies included in the sample. We assigned 62.2% of the companies one or more codes from the coding scheme. The cumulative percentages of sample companies that reached commercial use of AI, piloted AI, and mentioned AI during investor events were 40.6%, 19.8%, and 30%, respectively (Figure 6). These percentages reflect the highest code assigned to a company at a given time.

**Figure 6.** Cumulative percentage of companies by AI adoption phase.

Next, we validated the results and performed a post hoc analysis. First, we visually compared and assessed our results against those from survey studies, which we have identified in the first step of the procedure. Based on a visual inspection (Figure 7) as a means of informal validation, our results on ML use by companies aligned with the pattern of ML diffusion identified by the surveys. The alignment applies to both the levels and timings. Consequently, we concluded that the proposed method has the potential to supplement and, in some cases, substitute for the use of surveys in technology diffusion monitoring.
To further explore the results, we performed post hoc analysis, where we tested our findings against hypotheses generated from past literature. We derived the first null hypothesis from research on the differences in the rate of technology diffusion between companies from different sectors (Fichman, 2000; Greenhalgh et al., 2008, p. 139; Oliveira & Martins, 2011).

H1: There is no difference in the commercial diffusion rate of AI between companies from different sectors.

The second hypothesis came from background research on the impact of related knowledge, which in our case was represented as the digital intensity of firms (Calvino et al., 2018; Mucha & Seppälä, 2021), as one of the key determinants of organizational adoption of complex information technology (Fichman, 2000; Greenhalgh et al., 2008, p. 12; Pennings & Harianto, 1992).

H2: There is no difference in the commercial diffusion rate of AI between companies with different levels of digital intensity.

We performed statistical tests for stochastic dominance between the diffusion curves for companies representing different groups. These groups were industrial sectors for H1 and digital intensities for H2. To investigate stochastic dominance, we relied on the Kruskal–Wallis (KW) test, a nonparametric test that is suitable for use with multiple groups simultaneously (Mangiafico, 2016, pp. 248–261). As a follow-up to the KW test, we applied the Dunn test for

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1 Sources of survey results: McKinsey (Balakrishnan et al., 2020; Bughin et al., 2017; Cam et al., 2019; Chui & Malhotra, 2018); MIT (Ransbotham et al., 2017, 2018, 2019, 2020); O’Reilly (Lorica & Loukides, 2018; Lorica & Nathan, 2019; Magoulas & Swoyer, 2020).
pairwise comparison to determine stochastic dominance individually between each group (Mangiafico, 2016, pp. 255–256). Based, on this analysis we rejected both null hypotheses (see Table 6), thus supporting the notion that our proposed method generates results aligned with theory and, at the same time, providing more insights into our exploratory analysis of ML diffusion into commercial use by organizations.

Table 6. Results of Kruskal-Wallis tests.

<table>
<thead>
<tr>
<th>Test</th>
<th>chi-squared</th>
<th>df</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1: Kruskal–Wallis test for stochastic equality between the timing of commercial adoption of ML by different sectors</td>
<td>87.85</td>
<td>10</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>H2: Kruskal–Wallis test for stochastic equality between the timing of commercial adoption of ML by companies with different digital intensity levels</td>
<td>54.31</td>
<td>2</td>
<td>&lt; 0.001</td>
</tr>
</tbody>
</table>

Our subsequent analysis also indicates that the IT, financial, communication services, and healthcare sectors take ML into commercial use significantly earlier than companies in the real estate, materials, and utility sectors. In line with expectations, the results are consistent with past findings in the area of IT diffusion (Fichman, 2000). Significant variance in the rate of ML adoption is present even among S&P500 companies. In sectors where the pace of innovation is highest, commercial diffusion of ML is significantly higher than in traditional sectors where fixed assets are some of the key determinants of business success (Fichman, 2000). We also found that the commercial adoption of ML is related to digital intensity level. Groups of firms with higher digital intensity levels were significantly faster adopters of the technology. These results are consistent with past empirical findings for ML (Kinkel et al., 2021; Radhakrishnan & Chattopadhyay, 2020).

3.1.3 Addressing the research questions and contribution overview

Essay 1 contributes to technology monitoring research by advancing existing methodologies. It answers RQ1.1: How to extend content analysis methods for technology diffusion monitoring to account for multiple phases in the adoption of technologies into commercial use by organizations? As such, this essay is equally relevant to scholars and practitioners engaged in technology monitoring studies because both groups rely on a common set of methodologies (Roper et al., 2011, sec. 2.3).

In the essay, I propose a content analysis approach for technology diffusion monitoring that is suitable for technologies that have already entered the commercialization stage. Scholars developing technology monitoring methods have neglected this part of the technology life cycle with novel methods primarily focusing on pre-commercial stage technologies. The proposed approach fills this gap by concentrating on technologies that undergo commercialization or already are widely used.

The proposed method is versatile and can be applied to various technologies and contexts since it uses unstructured text as input and generates outputs in the form of technology adoption phases by an organization as defined by the researcher. Users of the method can adjust the content type and adoption phases to suit their research context. Thus, the method can complement studies on technology diffusion and adoption by organizations, which exceedingly rely on snapshot-in-time surveys (Rogers, 1983, p. 113). It is important to note that the proposed method can enrich the methodological toolbox because it has distinct characteristics from surveys. Due to relying on content analysis, the method can provide longitudinal and high-granularity results, which can be more frequent than surveys. Another advantage of the method is that its results are available without time lags commonly associated with periodic surveys. Next, unlike many commercially run surveys, the proposed method is replicable and does not require privileged access to information. For example, when applying the method in the context of ML diffusion, Essay 1 relied on transcripts of investor events, which are readily available from various databases. This also translates to replicability and transparency of the results.
Finally, recent advances in ML, such as large language models, might facilitate the implementation of the proposed method without the need for relying on human data coders. This can further increase the practical feasibility of employing the proposed method for technology diffusion monitoring by scholars and practitioners alike.

Furthermore, the essay answers RQ1.2: How have machine learning-based technologies diffused across different organizations? I apply the proposed method to investigate the process of ML technology diffusion by S&P500 companies. The results show that using publicly available information only – executive presentations and earnings calls, in this case – it is possible to generate diffusion curves that correspond to the results obtained from surveys run by consulting firms. At the time of analysis (the end of May 2019) the cumulative percentages of sample companies that reached commercial use of ML, piloted AI, and mentioned AI during investor events were 40.6%, 19.8%, and 30%, respectively.

3.2 Essay 2. Riding a bicycle while building its wheels: The process of machine-learning-based capability development and IT-business alignment practices

The objective of Essay 2 was to uncover the mechanisms inhibiting and promoting the successful development of organizational capabilities based on ML technologies. To meet this objective, we conducted an in-depth, longitudinal, and exploratory qualitative case study (Yin, 2009) of Finland’s AI Accelerator (FAIA). In contrast to Essay 1, which was a desktop study utilizing data from existing databases, work on this case study allowed me to observe first-hand and experience some of the complexities of ML adoption into organizational use.

3.2.1 Overview of data and method

FAIA was initiated and originally funded by the Finnish government in 2018 to facilitate collaborations related to ML, stimulate the adoption of the technology within the participating organizations, extract key lessons, as well as inform a broader audience of IT and business leaders in Finland on ML development, release, and operation. Firms participating in FAIA included some of the largest Nordic companies, such as Elisa (telecom operator), Nordea (bank), Posti (Finnish national postal services), S-group (retail chain), Telia (telecom operator), and YLE (Finnish national broadcasting company). Furthermore, multiple startups participated in FAIA in the role of ML service providers. FAIA participants formed several semiformal groups (batches), typically containing 4 to 8 members. Each batch focused on specific types of ML-based solutions or ML-related practices. The batches met regularly throughout the acceleration period for approximately six months. FAIA’s team facilitated and catalyzed collaboration by creating a community of practice with peer support and peer pressure.

Our data collection concentrated on FAIA, as the primary study setting. Since FAIA’s mission and activities revolved around the development of MLbC within its participating organizations, it allowed us to collect theoretically reliable and useful data (Eisenhardt, 1989). In the spirit of engaged scholarship (Van de Ven, 2007), I practiced participatory observation during FAIA’s weekly internal team meetings and workshops with the participating companies. Interviews with the participants and other experts were also utilized when collecting data within and outside of FAIA. I had unrestricted access to FAIA’s internal documentation and was copied on part of the emails between the FAIA team and the participating companies. During the data collection, I focused on developing insights into ML-related activities, events, their relationships, and their contribution to the development, release, and operation phases of MLbC. To complement our fieldwork centered on FAIA, we further engaged with organizations that were not affiliated with FAIA. These organizations included large corporations, consulting firms, and research institutions based in Europe, China, and the United States. We conducted interviews with employees in roles related to ML development, release, and operation at these non-FAIA-affiliated organizations. Data from these interviews allowed us to triangulate our analysis (Eisenhardt, 1989) by comparing insight against those from the data originating from FAIA – our primary study sample.
Table 7. Overview of data utilized in Essay 2.

<table>
<thead>
<tr>
<th>PHASE</th>
<th>SOURCE</th>
<th>METHOD</th>
<th>TOPICS</th>
<th>PURPOSE</th>
</tr>
</thead>
</table>
| Primary study data| Finland’s AI Accelerator (FAIA)                  | Participatory observation (N = 123) and interviews (N = 6) during the FAIA team’s internal meetings, workshops with the participating companies, and events arranged by FAIA (about 162 hours of events in total, of which about 61 hours audio recorded and transcribed), FAIA’s internal documentation (N = 62). | • Actors, technologies, tasks, and organizational structures involved in organizational ML initiatives  
• Organizational practices, approaches, and responses related to ML initiatives  
• Challenges and changes over time in relation to the topics listed above  
• Outcomes of ML initiatives | • Identifying the key themes for the organizational development of MLbC  
• Cross-comparison of different cases of MLbC development and deployment  
• Tracking that process over time and across multiple organizations to enable cross-comparison leading to comprehensive understanding |
| Confirmatory data | Non-FAIA affiliated organizations                | Semi-structured interviews with employees of non-FAIA-affiliated organizations (N = 20, about 13.5 hours of audio recording in total, transcribed). | • Actors, technologies, tasks, and organizational structures involved in organizational ML initiatives  
• Organizational practices, approaches, and responses related to ML initiatives | • Verifying the key themes for the organizational development and deployment of MLbC  
• Enriching data collection to allow triangulation based on data from outside of the primary study setting |
| Contextual immersion | Practitioner sources                   | Topic mining from practitioner sources (Gartner, MIT Technology Review, HBR, etc.) and ML-related podcasts (AI in Business, TWIML, Eye On AI, Practical AI, etc.). | • AI/ML-related activities, processes, challenges, and outcomes in organizations across industries and geographies  
• MLOps frameworks and practical experiences related to MLOps | • Sensitizing researchers to the emerging concepts and latest technical developments in organizational practices related to MLbC development |

To analyze the data, we relied on qualitative case study research processes (Eisenhardt, 1989; Yin, 2009). Figure 8 presents an overview of our analytical procedure. We started analysis during the data collection process to guide our discussions and interviews with the participants and to continue elaborating on finer details of the organizational process for the development of MLbC. Simultaneously, we engaged with multiple streams of literature that guided us in constructing the preliminary framings for the research problem and refining the research framework (Sarker et al., 2013). Furthermore, to deeply immerse ourselves in the topic, we followed practitioner publications and podcast interviews relevant to MLOps and ML use in organizations.

We analyzed the collected data in three phases—open coding, thematic analysis, and cross-comparison—to go beyond initial impressions and assume multiple perspectives on the evidence (Eisenhardt, 1989; Saldaña, 2015). Our analysis focused on three primary components: the significant milestones associated with the development of MLbC, the challenges faced during this process, and the various coping mechanisms utilized by the participating organizations to tackle these challenges.
3.2.2 Overview of findings

Our analysis delivered theoretical abstractions which can be summarized in the form of data structure visualizations, as presented in Figures 9-11.

**Figure 8.** Research procedure utilized in Essay 2.

**Figure 9.** Data structure in Essay 2 (Part 1).
Before presenting a conceptual model synthesizing our findings on the process of ML-based capability development and alignment (see Figure 12), I offer a quote, which provides a rich illustration of the phenomenon under investigation. This quote portrays the complex sociotechnical nature of MLbC development and the need for alignment across multiple cycles involved in the process.

*The management may be willing and mentally ready to start dealing with AI, but no one in the management can name a single application. The operative employees understand what data they have and do not necessarily have the capability of assessing how it affects their competitiveness if they make bigger investments. This conflict is constant. We are talking about a technology that requires cooperation from many parties in the organization: the one who understands what is valuable in the business, then maybe someone who is more of a visionary—what is worth pursuing in a certain number of years—and then some technological...*
people who can actually do that stuff, those who know the data, and so on. It requires cooperation from so many fronts.

Managing Director
AI consulting company

Figure 12. Machine Learning-Based Capability Development and Alignment Process Model.

We found that organizations which successfully develop MLbC advance sequentially and iteratively through (Re)Initiating, Effectuating, and Sustaining Alignment between their ML Organization, ML Technology, and ML User Cycles. Moreover, the success in this progression is governed by the interaction of two pairs of Structural Characteristics of MLbC (Temporal Complexity and Fostering Temporal Congruence) and Alignment Practices (Context Sensitivity and Cultivating Organizational Meta-learning).

At first, organizations (Re)Initiate Alignment by bringing together three building blocks—ML Organization, ML Technology, and ML User Cycles. This process requires Fostering Temporal Congruence to address the Temporal Complexity of aligning multiple cycles that might be iterating each at a distinct pace. Such an initial alignment relies particularly on synchronizing efforts and managing expectations. Forging new roles might also be required already at this phase. In addition, at this stage organizations discover and learn about how changes in various contexts might impact the future MLbC. Engaging in thorough data work typically characterizes this phase.

The Effectuating Alignment phase marks the transition of the envisioned MLbC into implementation and application in practical use. This transition is demanding in terms of fostering temporal congruence because synchronization of the cycles is critical to success in this phase. Furthermore, this phase is also the time when organizations can compare the (initial) performance of the MLbC with the expectations or targets. Also, employees with new roles can go beyond the preparatory work, thus engaging with the actual implementation and use of ML. This process necessitates learning and working with operational data in a production environment.

Finally, Sustaining Alignment coincides with the operational phase of the ML system. It requires reacting to changes in the external environment, the organization or the focal task. Such changes might also be more subtle and involve slowing down or speeding up the cycling pace.
of some of the constituent cycles, which might undermine the existing alignment of the cycles. Therefore, success in the MLbC development process at this phase requires being sensitive to context changes, which involves continuous learning about new ways of learning and working with data. Furthermore, in some cases, learning requires returning to one of the earlier phases in the MLbC development process.

3.2.3 Addressing the research question and contribution overview

Essay 2 answers RQ2: What mechanisms facilitate the development of MLbC? It disentangles the process of MLbC development and contributes to theory in three ways. First, it bridges the gap between research on MLOps and IS literature. MLOps research (Aguilar Melgar et al., 2021; Baier et al., 2019; Choudhary et al., 2022; Kolltveit & Li, 2022; Lwakatare, Crnkovic, et al., 2020; Lwakatare, Raj, et al., 2020; Muralidhar et al., 2021; Paterson et al., 2021; Renggli et al., 2021) oversimplifies and overlooks the organizational process of capability development, even when recognizing some organizational challenges related to MLOps (Mäkinen et al., 2021). This points to a gap that IS scholars recognize as the need to align tasks, technology, organization, and people (Lyytinen et al., 2020; Sarker et al., 2019). Essay 2 highlights the overlooked temporal and cyclical aspects of that alignment. By revealing this complexity, this study responds to a call for complexifying theorization of ML-related phenomena in organizations to grasp the underlying richness (Raisch & Krakowski, 2021).

Second, this study brings new insights to research on organizational capabilities that leverage ML technologies. Past research has already identified that the development of MLbC depends on an organization’s ability to select, orchestrate, and leverage specific tangible, human, and intangible resources (Mikalef & Gupta, 2021; Zhang, Pee, et al., 2021). Moreover, Essay 2 uncovers how the required resources could be combined and governed, as well as how this process leads to the creation of MLbC over time. Therefore, this study takes the IS conversation forward by bringing contextually rich and fine-grained insight and providing a much-needed explanation of mechanisms governing the MLbC development process.

Third, Essay 2 contributes to RBV and IT-business alignment literature. The process of resource structuring, bundling resources into capabilities, and eventually leveraging these capabilities by organizations has primarily been researched on the organizational or top management level (Sirmon et al., 2011). However, Essay 2 brings insights into the understudied topic of lower-level capability development within organizations.

3.3 Essay 3. Reframing machine learning systems through data work: A case study of a medical transcription company

The objective of Essay 3 was to uncover the organizational processes required for ML systems to function in novel operating environments or application domains. To meet this objective, we conducted an in-depth, longitudinal, and exploratory qualitative case study (Yin, 2009) at a start-up company, in which the small size and tight collaboration among employees allowed us to closely examine the continual reframing of an ML system for medical transcription. Essay 3 deepens the insights from Essay 2 by concentrating on context sensitivity, which is one of the structural characteristics inhibiting the successful development and alignment of MLbC. Our findings show how the case company was able to deal with context sensitivity through organizational data work.

3.3.1 Overview of data and method

The data for Essay 3 comprised materials providing insights into a single case study – ServCo (company pseudonym) and its proprietary ML-based system for automatic speech recognition (ASR). Since 2018, ServCo rapidly transitioned to utilizing the ASR, which assisted and sometimes substituted in-house transcribers by generating the preliminary text of the transcripts. Most of the transcription services performed by ServCo were medical transcriptions. A medical transcription is more than “just typing” the words dictated orally by doctors. Its diligent
execution requires extensive domain knowledge and involves a complex set of interpretative tasks in a demanding context (David et al., 2009), where the consequences of errors can be severe. To automate transcription and improve quality, ServCo developed and utilized ASR, which it viewed as a strategic asset. The system represented the state-of-the-art ASR technology and applied multiple neural network-based ML algorithms.

The case setting allowed us to investigate an ML system exposed to various input data distribution changes, which triggered the frequent need for system reframing. These changes were driven by the evolution and variety of the healthcare domains covered by ServCo, the company’s business needs, and its expansion to new languages and application domains. The case focused, therefore, on reframing challenges and processes, which gradually emerged as ServCo expanded and grew its service by attracting new and retaining existing customers. The criticality of successful ML system reframing was further magnified in this setting because the ASR played a vital role in the company’s business model, and any prolonged issues with reframing could threaten the company’s existence.

Table 8. Overview of the data for Essay 3.

<table>
<thead>
<tr>
<th>Data source</th>
<th>Content</th>
<th>Purpose</th>
</tr>
</thead>
<tbody>
<tr>
<td>The first round of interviews:</td>
<td>• 5 semi-structured interviews with medical doctors and transcribers not associated with ServCo&lt;br&gt;• 5 semi-structured interviews with ServCo’s employees</td>
<td>• Identifying the key themes related to ASR use in medical transcription&lt;br&gt;• Comparing manual and ASR-based transcription&lt;br&gt;• Probing the impact of ASR on medical transcription</td>
</tr>
<tr>
<td>The second round of interviews:</td>
<td>• 20 interviews (14 semi-structured and 6 informal) with ServCo’s employees&lt;br&gt;• 4 semi-structured interviews with ServCo’s customers</td>
<td>• Generating rich and nuanced insight into the ASR reframing process across multiple reframing rounds&lt;br&gt;• Cross-comparison of responses from the perspective of multiple interviewees</td>
</tr>
<tr>
<td>• A workshop with ServCo’s employees</td>
<td>• Group brainstorming and a joint reflection session on ServCo’s approach to reframing ASR to new application domains</td>
<td>• Verifying key themes and developing further insights on ASR reframing through data work&lt;br&gt;• Engaging with practitioners to stimulate their self-reflection</td>
</tr>
<tr>
<td>ServCo’s internal documentation:</td>
<td>• 14 transcription guidelines for data operators</td>
<td>• Enriching data collection and enabling cross-comparison with interview data&lt;br&gt;• Uncovering details of data work</td>
</tr>
<tr>
<td>Examination of and interaction with ServCo’s ASR</td>
<td>• Generating real-time transcripts from dictations (both within and outside of healthcare domain)</td>
<td>• Replication of ASR responses described during the interviews&lt;br&gt;• Role-play and immersion into the tasks of data operators, data scientists, and doctors</td>
</tr>
<tr>
<td>Publicly available archival documents:</td>
<td>• History of ServCo’s development and exposure to various application domains (both within and outside of the healthcare domain)</td>
<td>• Verification of reframing success evidenced by business growth&lt;br&gt;• Identification of useful facts for eliciting informative responses during the interview</td>
</tr>
</tbody>
</table>

Data collection (see Table 10) took place during 2022-2023. We conducted 34 interviews (28 semi-structured and six informal) and a workshop with the case company, which allowed us to interact with each of ServCo’s employees at least once. The initial five interviews were conducted with doctors and transcribers not associated with the company or their ASR to build a broader understanding of the medical transcription task. Next, we conducted interviews with the case company employees and customers. We also had unrestricted access to ServCo’s internal documentation, which covered guidelines for data operators on how to conduct transcription for specific types of customers (14 documents). Furthermore, we collected 40 public documents, including news articles mentioning the company and publications by the company, as well as LinkedIn posts created by the company employees. Finally, we received access to the ASR via a real-time transcription service, which allowed us to replicate some of the system
behaviors or outputs discussed during the interviews, as well as witness how the ASR responded to different speaker accents (authors have different native languages).

The case analysis approach (Eisenhardt, 1989; Yin, 2009) we took can be seen as abductive (Sarker et al., 2018). The analysis evolved through our increased engagement with and understanding of the empirical material, emergence of identified themes and categories, simultaneous triangulation with literature salient to understanding ML systems, data work, and IT re-framing, and, finally, informed by frequent analysis sessions among the research team. Given the exploratory nature of our research (Eisenhardt, 1989; Yin, 2009), we started analysis while gathering data to guide our research focus and update the interview questions. The themes of the interviews changed throughout the study and started from probing the impact of the ASR on medical transcription and ended with a focus on ML system re-framing through data work and related challenges. In the first round of analysis, we utilized open coding for all the materials collected up to that point (Saldaña, 2015). At that stage, the first two authors coded the collected data first independently and then jointly (Saldaña, 2015). The most prominent themes included “context switching,” “algorithm learning,” and “learning from data.” We focused on exploring these themes in detail while conducting the remaining interviews. Next, we continued to collect more data and also re-coded all of the interview transcripts and archival documents using a focused coding approach (Saldaña, 2015), which surfaced that “system re-framing” through “organizational data work” represented the central theme that heavily influenced the transcription service as it evolved to cover new medical specializations and other use cases. Furthermore, the notions of “control and efficiency of data work” vividly surfaced throughout our empirical material. No new themes emerged in the latter part of this interviewing and coding round, thus indicating theoretical saturation (Eisenhardt, 1989). At that stage, we also heavily relied on visual mapping to move from raw data and individual themes to the abstracted conceptualization of ML system re-framing through organizational data work. During the final round of analysis, we conducted theoretical abstractions and conceptualized types of data work constituting ASR re-framing.

3.3.2 Overview of findings

Table 9 summarizes the final data structure resulting from the analysis. It outlines four types of data work necessary to reframe ServCo’s ASR and the fifth category, which represents the simultaneous need to balance control and efficiency in that data work.

Our study revealed that ML system re-framing is constructed through organizational data work that continuously shapes the system training data (Figure 13). Four types of data work constitute this process: (1) generating training data, (2) establishing data quality and coherence, (3) spotting out-of-frame data, and (4) addressing data gaps. Furthermore, the outcomes of re-framing depend on the ability of system developers to balance two aspects of data work, namely control over its inputs and outputs and its efficiency. Jointly, these aspects determine whether and how organizations can re-frame their ML systems when faced with changing data distributions.

Generating training data involves reviewing data inputs and outputs, as well as editing and recording data. This data work can be considered an initial step of the re-framing process because it creates data which will be used in future rounds of system retraining. Generating training data is an organizational, and not just technical, process because it necessarily involves human decision-making – either in real-time when ServCo’s data operators evaluate the data or even earlier when designing which types of data to collect and how to approach it. Therefore, the very act of data generation is shaped by the organizational priorities, focus, level of understanding, as well as plans and ambitions.
<table>
<thead>
<tr>
<th>Concepts</th>
<th>Subcategories</th>
<th>Data Work Categories</th>
<th>Example quotes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Listening to audio recordings</td>
<td>Reviewing data inputs and outputs</td>
<td>Generating training data</td>
<td>“Before I start listening, I skim the text to see if the sub-headings are correct. Once I know how the structure looks like, then I start listening to it from the beginning.”</td>
</tr>
<tr>
<td>Reading preliminarily generated transcripts</td>
<td>Editing and recording data</td>
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<tr>
<td>Correcting spelling and wrong words</td>
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<tr>
<td>Adding tags describing the content of recordings</td>
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<tr>
<td>Capturing data in own system</td>
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<td></td>
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<tr>
<td>Investigating unfamiliar words as they appear</td>
<td>Ensuring completeness and correctness</td>
<td>Establishing data quality and coherence</td>
<td>“When you introduce speech recognition, then the need for language harmonization appears immediately. Secretaries shouldn’t transcribe words the way they feel like doing it, but rather, everyone should transcribe them the same way, every day.”</td>
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<td>Multiple quality checks</td>
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<tr>
<td>Selecting people with a quality preference</td>
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<tr>
<td>Selecting which websites to trust</td>
<td>Picking sources of truth</td>
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<tr>
<td>Asking for guidance from third parties</td>
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<tr>
<td>Researching and selecting linguistics and grammar rules</td>
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<tr>
<td>Creating guidelines</td>
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<tr>
<td>Discussing and sharing best practices on Slack</td>
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<tr>
<td>Educating external users about standardization</td>
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<tr>
<td>Checking consistency of terminology by supervisors</td>
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<tr>
<td>Internal data operators reporting common issues</td>
<td>Spotting by users</td>
<td>Spotting out-of-frame data</td>
<td>“The transcribers might notice issues that are not reflected in the data or that to me [as a data scientist] look correct or as minor issues only. But then the transcribers would say that it is wrong.”</td>
</tr>
<tr>
<td>External users sending “issue reports”</td>
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<tr>
<td>Status meetings with customers</td>
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<tr>
<td>Generating reports on frequently misspelled words</td>
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<tr>
<td>Checking word error rates for re-trained models</td>
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<tr>
<td>Comparing statistics between different models</td>
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<tr>
<td>Using the latest 24-hour data to verify performance</td>
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<tr>
<td>Introducing “training jobs”</td>
<td>Generating and sourcing additional data</td>
<td></td>
<td>“Whenever there are no jobs to transcribe for any paying customers, we’re using our transcribers to transcribe the dictations that customers dictated through our real-time transcription service, so that we are able to learn from that.”</td>
</tr>
<tr>
<td>Generating synthetic data</td>
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<tr>
<td>Hiring medical students to read transcripts</td>
<td>Encoding expert knowledge as rules</td>
<td>Addressing data gaps</td>
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<tr>
<td>Hard-coding sound to text mappings</td>
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<tr>
<td>Cleaning and re-purposing data from customers</td>
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<tr>
<td>Hard-coding capitalization rules</td>
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<tr>
<td>Branching to a separate model</td>
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<tr>
<td>Adding new types of configurations to accommodate a wide range of use cases</td>
<td>Increasing system flexibility</td>
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<tr>
<td>Automating rule creation based on new patterns emerging in the training data</td>
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<tr>
<td>Dynamic slicing of audio to get more 100% correct training data</td>
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<tr>
<td>Gaining access and permission to data</td>
<td>Control over data work</td>
<td>Balancing data work</td>
<td>“We don’t have any control of the external users. Some are saying one sentence and then pressing the pause button and then putting it on again, because they got used to that with physical recorders. They don’t need to do that, but that’s their workflow.”</td>
</tr>
<tr>
<td>Giving out control by allowing external data operators</td>
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<tr>
<td>Losing the ability to capture data in real-time service</td>
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<tr>
<td>Regaining control through “training jobs”</td>
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<tr>
<td>Monitoring transcription time multiple (TTX)</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Tripling the efficiency of internal data operators</td>
<td>Efficiency of data work</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Customers do the data work</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Using internal slack/overcapacity to do the “training jobs”</td>
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</tbody>
</table>
Establishing data quality and coherence was instrumental for ServCo to reach the level of accuracy demanded by healthcare professionals, who represented a majority of the company’s customers. This data work involved ensuring completeness and correctness, picking sources of truth, and enforcing coherence. Given the importance of data quality in ML system training it is necessary to achieve a sufficient level of completeness and correctness to maximize the achievable ML model performance gains. Yet, the very act of ensuring completeness and correctness is not absolute in nature. In many organizational tasks where ML is used, in general, and specifically in medical transcription work performed by ServCo, there is often more than one correct interpretation of which data outputs should be matched with a given data input. Thus, ServCo’s data operators had to pick sources of truth based on which they could decide how to “correctly” perform their data generation work. Since it is not possible to predict all types of decisions that need to be made during that process, data operators had to use their judgment when selecting sources of truth. Therefore, ServCo sought to continually enforce coherence in data work across different data operators. This effort aimed at aligning the unique approaches to the transcription efforts of individuals and reducing variance in the outputs.

Another layer of organizational data work consisted of spotting out-of-frame data, which dealt with data that was already created and used in the previous rounds of ASR retraining. Both users and data scientists participated in this type of data work. Whenever users noticed that ASR consistently transcribed certain words or phrases incorrectly, they notified data scientists. To complement spotting errors by users and to extract more insights from the data ServCo was accumulating, also data scientists engaged in spotting out-of-frame data. In performing that work data scientists relied on scripts and other forms of automation, so that they could process large volumes of data in short periods of time. However, they also investigated individual data points and checked for common error patterns manually.

Addressing data gaps constituted the last type of data work contributing data and its quality directly to the retraining of the ASR, which allowed the system to be reframed. To address the gaps identified by spotting out-of-frame data, ServCo relied on generating and sourcing additional data, encoding expert knowledge as rules, and increasing system flexibility. The case company engaged in multiple approaches to either generate or source additional data – they created synthetic or simulated data by themselves, hired medical students to read existing texts of medical records, or sourced data from customers’ historical records. To speed up fixing a recognized data gap, ServCo occasionally used manual rules stating the correct output.
Similarly, they relied on their in-house expert knowledge or guidance received from external sources and encoded them into rules, which shaped how certain data inputs and outputs should be matched. Finally, ServCo constantly searched for ways to increase system flexibility by, for example, re-evaluating past decisions regarding steps in the data processing pipeline to increase the share of audio recording time that is guaranteed to have high-quality transcripts. They also increased the system flexibility by creating dedicated models for specific use cases, which allowed for achieving better performance thanks to using more representative data specific to the selected use cases.

Balancing control over and efficiency of data work constituted a regulating function which impacted all other types of data work and determined the overall reframing process. Control, in this case, refers to the level of oversight and influence that ServCo exercises on who, where, when, and how interacts with which data. Efficiency of data work stands for the time and resources invested into that work. The case company could, for example, select between multiple approaches to generating the training data. They could achieve a high degree of control if the internal data operators carried out that data work. However, this approach also required a higher commitment of resources and, in some cases, was slower than relying on external data operators, even if they delivered lower-quality data. Therefore, balancing data work emerged as an essential element of the overall data work.

3.3.3 Addressing the research question and contribution overview

Essay 3 answers RQ3: How do organizations reframe their operational ML systems through data work to retain ML system performance? The essay contributes to theory by unpacking the organizational process of ML system reframing and highlighting the role of various aspects of data work. First, the study bridges two novel and rapidly advancing streams of literature concerned with ML systems and data work. The essay draws attention to data work’s criticality in ML systems in general and its vital role in reframing them. While prior research recognizes that data work includes multiple activities, it primarily discusses the work performed by data managers, analysts, or scientists (Bossen et al., 2019; Grønsund & Aanestad, 2020; Mikalsen & Monteiro, 2021; Mucha et al., 2023; Parmigiani et al., 2022). Essay 3 shows ways in which data work involves individual and group activities and is located both within and outside the organization. This data work creates a unique social signature on the ML system itself. Multiple minor steps performed by various actors unfold, i.e., when to check the correct spelling of a word with colleagues versus relying on one’s memory, which generates and shapes the training data sets.

Second, Essay 3 extends the current understanding by connecting the IT reframing problem with the notion of data work. This view of reframing significantly differs from traditional IT reframing, which relies on explicit codification of domain knowledge translated to instructions in the software (Salovaara et al., 2019). Reframing ML systems, on the contrary, is continual and unfolds through a longitudinal process of generating and gathering training data, which shows how the system should perform its task. ML system reframing, thus, is not explicit but rather emerges inductively from data. This creates novel challenges for organizations because reframing is no longer an act of translation – from developers’ domain understanding to code – but rather a diffused and fragile social process with unique intricacies and complexities.

Third, the study reveals that ML system reframing success depends on continuous balancing between control and efficiency of data work. The four types of data work we identify cover the full lifecycle of an ML system operation (Paterson et al., 2021). These four are relevant to any type of ML system reframing problem due to changes in input data distribution. Yet, knowing what types of data work constitute ML system reframing is just a starting point – organizations must also determine who, where, when, how, and at what cost will engage in that work. Therefore, the need to balance control and efficiency of data work underlying the reframing process is tightly interrelated with the four types of data work, which we identified.
4. Discussion

Throughout the development and writing of this thesis, few technologies have been receiving as much attention from business leaders, the press, and the public as ML. For example, in late 2022 OpenAI launched ChatGPT, a chatbot which is built on a large language model and allows users to engage in unscripted and open-ended conversations or instruct it to perform a variety of tasks. The application reached 100 million users in the first two months (Milmo, 2023). This achievement made it the fastest-growing consumer internet application in history (Milmo, 2023). The resulting wave of interest in generative AI only further fueled the imagination and ambition of many leaders to take ML technologies into use in their organizations. This is evidenced by the global corporate investment into ML-related activities exceeding USD 100 billion every year for the past three years (Maslej et al., 2023, sec. 4.2).

However, a wide range of technology applicability and investment of substantial resources do not immediately translate into improvements in productivity, profitability, value creation, or other measures of organizational performance (Brynjolfsson et al., 2018). Indeed, many organizations fail to generate meaningful outcomes from their ML initiatives (Ransbotham et al., 2018). These challenges are grounded in the fundamentally different nature of ML systems when compared to traditional IT systems – they are not explicitly programmed, but rather trained with data.

Organizational and IS scholars have recognized that this novelty not only provides an opportunity but also makes it an imperative, to revise and advance our understanding of how modern-day technologies, such as ML, interact with and shape work in organizations (Benbya et al., 2021; Berente et al., 2021; Lyytinen et al., 2020; Raisch & Krakowski, 2021). In this section, I provide an overview of implications for research and practice arising from this thesis. I conclude the discussion by reflecting on the limitations of my research and the opportunities for future research.

4.1 Implications for research

The overarching objective of this thesis was to explore the processes of how organizations can successfully develop, use, and cultivate over time ML-based capabilities. When considered holistically, my research meets this objective by providing new insights into the processes of ML technology diffusion into commercial use by organizations, the development of MLbC, and the reframing of the underlying ML systems. These processes are inherently interwoven with each other, which I visually present in Figure 14.

First, organizations familiarize themselves with the new technology, start considering it, and experiment with it. The ensuing commercial use unfolds thereafter. The top section of the figure demonstrates that companies do not necessarily publicly reveal this progression in the same sequence as how they progress through these phases. One reason behind this is that not all commercial uses of technology are equally salient to organizational success. Particularly notable is the distinction between ad hoc execution of tasks using available resources, including technology, and the development of organizational capabilities (Helfat & Winter, 2011) based on these technologies. This latter use of technology might determine organizational performance and competitiveness (Sirmon et al., 2007).
Figure 14. The interrelationships between the processes of ML technology diffusion into commercial use by organizations, development of MLbc, and reframing of the underlying ML systems.
Next, as presented in the middle section of the figure, my research zoomed in on the process of MLbC development, which I studied in multiple organizations. The results indicate that the MLbC development process iteratively unfolds through three alignment phases: (1) (Re)Initiating Alignment, (2) Effectuating Alignment, and (3) Sustaining Alignment. The alignment process itself concerns three constituent cycles, which organizations need to align together to create MLbC. These cycles represent a series of successive changes experienced by ML Organization (e.g., data science teams), ML Users, and ML Technology. Reaching and sustaining alignment is not easy, because of the structural characteristics of MLbC which inhibit alignment. These characteristics are Temporal Complexity and Context Sensitivity. Organizations which succeeded in MLbC development relied on two sets of practices to tackle the inhibiting characteristics. These sets of practices were Fostering Temporal Congruence (through synchronizing efforts, forging new organizational roles, and managing expectations) and Cultivating Organizational Meta-learning (learning to learn and embracing data work).

Finally, given the importance of data to ML system development and the sensitivity of MLbC to changes in the operational context, which determines the data, my research also unpacked the underlying process of ML system reframing. The case company, over the period of five years, continued to expand its medical transcription service offering to an increasing range of customers representing different medical specializations, languages, as well as a variety of recording types (dictations, phone calls, podcasts, video subtitling). To grow the business and ensure the viability of the company, the automatic speech recognition system, which was based on ML, had to be frequently reframed to new operating contexts or application domains. Succeeding in reframing required from the case company dedication of resources and attention to data work generating the inputs necessary for successful retraining of the underlying ML algorithms. It involved balancing control over data work and the efficiency of that work. Thus, such balancing meant deciding who, where, when, how, and at what cost will engage in data work. In particular, the study found that the required data work consisted of (1) generating training data, (2) establishing data quality and coherence, (3) spotting out-of-frame data, and (4) addressing data gaps.

These insights, in combination, contribute to research in two important ways. First, my thesis contributes specifically to research on ML in organizations, which is a rapidly emerging stream of literature. Second, my work brings new insights extending a broader set of background literature within organizational and IS research. I discuss these contributions in the next two subsections.

4.1.1 Contribution to research on ML in organizations

This thesis responds to the call for embracing the complexity of AI in organizations (Raisch & Krakowski, 2021) and uncovers the processual nature of ML adoption, development, use, and cultivation in organizations. Thus, my overall research extends the emerging scholarly conversation on ML in organizations (Ågerfalk, 2020; Benbya et al., 2021; Berente et al., 2021; Lyytinen et al., 2020).

Unpacking ML in organizations and the related underlying complex processes

When considered jointly, the essays reveal the complexity of how ML adoption, development, use, and cultivation processes unfold – they are not atomic events but rather rely on multiple actors in organizations engaging in diverse types of work over extended periods of time. This is especially the case for continually learning ML systems, which are never ready and are always catching up with the operating environment. While Raisch and Krakowski (2021) argue that managing AI relies on balancing automation and augmentation, which might involve temporal separation of these two modes of technology use, my work shows that both automation and augmentation by themselves are characterized by temporal complexity. Recognizing the inherent contingency of ML system development and use in organizations on how these processes unfold over time is important, because the timing of decisions, actions, and outcomes do not necessarily coincide within ML Technology, ML Organization, and ML User cycles. This structurally inhibits the alignment of these three constituent cycles of MLbC. Furthermore, the operating environment or application domain for any ML system might be suddenly disrupted because of a change in the task, organization, or external environment context. Such context
sensitivity is more challenging than in the case of traditional IT systems because ML systems might learn to give the right results for the wrong reasons or might satisfy the training objectives without accomplishing desired tasks in practice. Such development might be difficult to detect and, in the longer term, might create vulnerabilities and systemic failures of capabilities. Overall, these insights contribute to the emerging understanding of organizational processes around ML (Gronsund & Aanestad, 2020; Ruissalo et al., 2022; Strich et al., 2021; van den Broek et al., 2021; Waardenburg et al., 2022).

**Organizational cultivation of ML systems leads to idiosyncrasy in MLbC**

Maintaining the alignment between the three cycles of MLbC corresponds to what Lyytinen and colleagues (2020) refer to as cultivating ML systems. Such cultivation builds capabilities through “mindful enhancement of learning by setting up the right conditions” (Lyytinen et al., 2020, p. 10). My study of a medical transcription company shows that such cultivation unfolds through organizational data work, which necessarily situates the process within the unique social context of the organization performing that work. My subsequent theorization of this process reveals that considering the uniqueness of ML systems is not limited primarily to the question of the uniqueness of data as such. Instead, an ontological perspective which emphasizes the processual nature of the world enriches our insight into this question. It reveals that the sources of idiosyncrasy in organizational capabilities which are based on ML are in the organizational process shaping the data. Thus, this thesis extends the emerging research on organizational capabilities which are grounded in ML technologies (Mikalef et al., 2023; Mikalef & Gupta, 2021) and complements the understanding of the sources of value in organizational use of ML (Shollo et al., 2022).

**Reframing ML systems reinforces organizational learning**

Case studies carried out within the scope of this thesis find that organizations which were successful in developing, using, and cultivating MLbC actively engaged in reframing their ML systems through organizational data work. These empirical results provide further evidence and go beyond what can be derived from simulations (Fügener et al., 2021; Sturm, Gerlach, et al., 2021), conceptual modelling (Balasubramanian et al., 2022), or experiments (Fügener et al., 2021). My empirical studies indicate that when context changes are frequent or significant, organizations need to embrace data work and actively realign their ML systems with human understanding of the context. As such, these can be seen as ML system reconfiguration, which is defined as “activities aiming to realign a productive ML system with humans’ current problem understanding” (Sturm, Gerlach, et al., 2021, p. 1586). Such reconfiguration becomes instrumental in facilitating and directing organizational learning because it reflects the efforts in encoding existing human knowledge into ML systems and also allows human actors to benefit from that knowledge (Sturm, Gerlach, et al., 2021). These insights bring important evidence to the ongoing debate concerned with the implications of ML system use on organizational learning (Balasubramanian et al., 2022; Fügener et al., 2021; Lindebaum et al., 2020; Sturm, Gerlach, et al., 2021). My work suggests that it is essential to consider the organizational setting and processes to evaluate such implications. Specifically, the pivotal role of ML system reframing and, thus, organizational data work unfolds through a complex set of human-to-human and human-technology interactions which are deeply interwoven with each other, temporarily related, and rely on imperfect instructions. Therefore, the notion of balancing control and efficiency in organizational data work becomes a regulating function, which greatly influences the success of ML system reframing and, thus, related organizational learning. My results indicate that when an organization can find the right balance of control and efficiency in data work it can successfully learn and reframe its ML system so that it can perform in a dynamic operating environment where consequences of errors are severe.

**The shaping of ML system agency unfolds through organizational data work**

Finally, my work extends the emerging research concerned with the agentic properties of ML systems (Baird & Maruping, 2021; Murray et al., 2021). These systems have agentic properties because they often are not fully transparent or understood by the users (Berente et al., 2021). Furthermore, they participate in delegation relationships with humans (Baird & Maruping, 2021; Berente et al., 2021; Murray et al., 2021). Delegation involves giving up some control to
gain efficiency in task execution (Baird & Maruping, 2021). Yet, once some control has been assumed by an ML system, the agentic properties of that system are not necessarily static. Stemming from my research, both the notion of alignment of three cycles in MLbC (ML Organization, ML Technology, and ML User) and that of reframing ML systems through organizational data work suggest that the shaping of ML systems is open-endedly allocated to the focal organization and not explicitly confined to specific role, such as software developers in traditional IT systems (Kudaravalli et al., 2017; Salovaara et al., 2019; Volkoff et al., 2007). Rather, the endowments (Baird & Maruping, 2021) of the underlying ML system – what it is capable of performing and how – are constructed within an organization through its practices. For example, ways of working, commitment to delivering quality results, and personal preferences of employees performing tasks which are later used for ML system retraining might shape the future behavior of the ML system. Hence, my work challenges the view that through organizational use of ML systems we can fully detach the locus of agency in protocol development (Murray et al., 2021) – selecting what and how should be done in organizations – from human actors. Instead, the unique organizational approach to cultivating organizational meta-learning and, especially, organizational data work determines how the ML systems are nudged to create frames defining their inferential logic for task execution. This offers a new and more organizationally situated perspective on how agentic properties of ML systems emerge and change over time.

4.1.2 Broader implications for organizational and IS research

Research on how technologies diffuse into organizational use (Dosi, 1982; Rogers, 2010; Tornatzky et al., 1990), how well they fit with tasks and users (Goodhue & Thompson, 1995), and how they influence and shape organizational capabilities and performance (Bharadwaj, 2000; Helfat et al., 2009; Sarker et al., 2019; Winter & Nelson, 1982) constitutes an important part of foundation to both organizational and IS scholarly endeavor. My research contributes to this cumulative tradition by focusing on and examining technologies which are different from all other technologies thus far. ML systems can perform their tasks not exclusively because engineers designed them and encoded instructions into their inferential logic, as is the case with other digital technologies. Instead, ML systems learn from training examples (Brynjolfsson & Mitchell, 2017). This learning process can be reiterated while the ML systems are already in operational use, thus making them non-deterministic – at different points in time the same system might provide different outputs even if presented with the same inputs.

Extending theorizing of non-deterministic technology development-in-use in organizations

Considering the non-deterministic nature of ML systems constitutes an important extension of existing research because past digital technologies were explicitly programmed by developers (Autor, 2014; Brynjolfsson & Mitchell, 2017) and past theorizations across organizational and IS literature predominantly assumed technology to be static (Lyhtinen et al., 2020). The default view in many studies has been and continues to be that technology is stable once it is developed and implemented in an organization (Anthony, 2021; Beane, 2019; Mazmanian et al., 2013). Even when organizational and technology change is in focus, the technology is assumed to change only when developers explicitly make the changes in the underlying source code (Lyhtinen & Newman, 2008; Volkoff et al., 2007). This has been recognized as a challenge and an opportunity for theory development (Glaser et al., 2021; Gronlund & Aanestad, 2020; Hyysalo et al., 2019; Lyhtinen et al., 2020; Sturm, Koppe, et al., 2021). Thus, my unpacking of the processes of MLbC development and ML system reframing through data work brings new insights into theories developed during an era of deterministic technologies. In particular, my work extends the research on organizational capabilities and their development to the context of ML (Amit & Schoemaker, 1993; Bharadwaj, 2000; Helfat et al., 2023; Helfat & Peteraf, 2003).

Distinct patterns in ML system usage

Cyclical development of ML systems and change in their capacities and endowments (Baird & Maruping, 2021) implies iterative adoption by users – they might periodically restart and re-
live the technology adoption process when the ML system changes. This can be triggered by changing perceptions of the relative advantages of the ML system when compared against existing alternatives (Fichman, 2000). This resonates with the temporal complexity of MLbC development because individual users might respond differently to systems that produce continually changing responses, even if provided with the same inputs. For example, graphic designers relying on Midjourney to generate images as inputs to a book cover or a movie poster design might undergo adoption and abandonment of the technology for specific tasks within their design workflow several times and at various intervals. Furthermore, the range of ML system features they utilize might also oscillate over time and may necessitate continual or periodic exploration of what is possible. Such changes reflect that considering how well ML systems fit with the underlying task and users might require a more dynamic perspective than traditional IT systems (Goodhue & Thompson, 1995). This suggests that the pattern of initially exploring features of technology and later narrowing down the usage practices (Benlian, 2015) might not hold for ML systems that continue to learn. Instead, usage patterns of these systems might present more complex patterns and pathways.

Evolution and propagation of organizational practices via ML system adoption and use

The need for aligning ML User, ML Technology, and ML Organization cycles through the underlying data work suggests that the re-invention or “the degree to which an innovation is changed or modified by a user in the process of its adoption and implementation” (Rogers, 1983, p. 175) is recursive and evolves over time for ML systems. This process has the potential to be more dynamic for continually learning ML systems than for any traditional IT system because changes in ML system behavior can materialize without any need for modifying software code by developers (Brynjolfsson & Mitchell, 2017). Hence, in some cases, ML users might have a greater influence on shaping their digital tools than other existing digital solutions. This increasing role of how the performance of organizational practices changes digital technologies and organizations informs our understanding of technological embeddedness and organizational change (Volkoff et al., 2007). As an extreme and informative example, we can consider the case of Twitter users “poisoning the character” of Microsoft’s Tay bot – the interactions of the bot with people made it racist in less than a day (Neff, 2016). However, changes in ML system performance due to user interactions might be more subtle. For example, in my study of the medical transcription company, in some cases, data created by users other than in-house data operators resulted in the ML system learning incorrect spellings of medical terms. While in this case study the errors were detected and corrected by other users, such an outcome is not always guaranteed. Therefore, ML system adaptation and re-invention are more complex than that of other technologies. Uncovering this recursive process is particularly important because when ML systems learn new behaviors they can propagate them to other users, thus spreading and shaping organizational practices in a more dynamic and inductive manner than explicit changes of traditional IT systems.

4.2 Implications for practice

In line with the engaged scholarship approach (Van de Ven, 2007), which I assumed in my research, this thesis also brings implications for practitioners. The insights from my work are timely and relevant because many organizations struggle with generating value from their ML initiatives (Ransbotham et al., 2019). This indicates that the lack of understanding of how to develop and maintain ML-based capabilities is prevalent in practice.

Not a single task, but an ongoing complex effort

The MLbC development process is not a single task or project that can be completed once and for all. It is an ongoing and complex effort that requires managers to acknowledge this reality and change the current situation. My research indicates that adhering to MLOps practices in the entire lifecycle of ML systems, from development to release to operation (Choudhary et al., 2022; Lwakatare, Crnkovic, et al., 2020; Mäkinen et al., 2021; Paterson et al., 2021) is insufficient for building successful MLbC. Managers also need to adopt a cyclical approach in two other domains, besides the MLOps perspective that corresponds to the ML
Technology cycle. These are the ML Organization and ML User cycles, which are also part of MLbC. Cyclicality in all three components of MLbC should be considered and accepted by those who are responsible for developing and utilizing organizational capabilities that rely on ML technologies as a key resource. The importance of iterations in technology development is well-recognized, but the same cannot be said for the continual changes in the other two cycles. Ignoring the ongoing evolution of these cycles results in misalignment and jeopardizes the overall effectiveness and longevity of MLbC. My work identifies individual MLbC alignment practices and provides empirical examples that can guide organizational leaders in overcoming structural barriers to aligning the three cycles that makeup MLbC. A key factor for success is to manage the timing and pace of decisions, actions, outcomes, and iterations. For example, when a data science team can quickly update an ML model based on the data patterns they observe, the users also need to learn and adapt to the ML system’s changing behavior faster. To achieve this alignment between ML Users and ML Technology, one solution is to create new roles in the teams, such as “AI ambassadors,” who are operational employees training and motivating their peers to use ML systems daily.

Context sensitivity of ML systems magnifies the importance of data in organizations

The sensitivity of ML systems to context change is another key area that this thesis highlights. Organizations in volatile environments need to consider this aspect. They need to reframe the system to make it function in such environments. Reframing involves more than retraining the ML model technically. It also involves investing in data work. Data work includes generating data effectively, ensuring data quality and coherence, identifying out-of-frame data, and filling data gaps. These are essential to maintain the performance of the ML system. Managers must be able to control the data work and its efficiency. Thus, data scientists or IT departments cannot be solely responsible for reframing. Having an ML system "owner" who checks the data, talks to the users, updates the system specifications, and looks for someone to make the changes is also not enough. Instead, data work is the key to successful ML system reframing – it unfolds through usage, influences system operation and subsequent use. Traditional IT system maintenance differs from this, as usage and development are more distinct. Minor data work details can have a major impact on how ML systems evolve over time, as they result from multiple choices at the level of individual data points. Managers should not only foster joint work practices among data scientists, domain experts, and users (Asatiani et al., 2021; Grønsund & Aanestad, 2020; van den Broek et al., 2021) but also embrace a data-centric perspective on organizational work as a whole.

4.3 Limitations and future research

Engaging in any research project involves making choices, balancing trade-offs, and selecting the scope of work. Therefore, inevitably limitations are associated with any such undertaking. This thesis has several limitations, which also indicate opportunities for future research. In this section, I discuss these limitations and suggest topics for further investigation. By doing so, this discussion also signals to managers and policymakers areas that require careful attention, because of their importance and, at the same time, their limited understanding.

First, the empirical material for this thesis was collected primarily from Finland and the USA. These two countries are not representative of the entire world and particularly not of the developing countries. My research points out meaningful differences in the ML diffusion rates between companies from different industrial sectors and between those representing distinct levels of digital intensity. Recognizing these differences is important because there is significant variance in the engagement of various nations and regions in certain industrial sectors and the wide distribution of digital intensity of firms within a single sector and across countries (Calvino et al., 2018). Furthermore, since ML technologies can be considered general-purpose technologies (Bresnahan, 2010; Goldfarb et al., 2023), commercial diffusion of ML technologies can meaningfully shape the future of firm-, sector-, and nation-level competitiveness. Particularly, countries with highly concentrated industrial sectors and which do not have firms with high levels of digital intensity are at risk of falling behind in their ability to compete (Calvino & Criscuolo, 2022). Therefore, studies on ML diffusion which cover multiple nations or
regions can bring important insights into this topic. Furthermore, for managers and policymakers, it is becoming increasingly important to understand what aspects of firm digitalization foster ML diffusion that translates to commercially meaningful outcomes. Therefore, future research should investigate not only the diffusion of ML technologies in different regions of the world, but also the process of MLbC development and, especially, inhibiting factors and coping mechanisms used by firms from different countries and sectors. The resulting insights could generate transferrable lessons for practitioners and inform the theorizing of MLbC.

Second, this study focused primarily on organizations developing MLbC with the use of significant in-house resources. This was evidenced by many firms covered in this research maintaining their ML organization and developing tailor-made technology. However, many organizations globally rely on externally developed technologies and are more passive receivers of ML technology. Furthermore, continuous development of ML makes it more accessible and more productized, thus allowing usage even with more limited in-house knowledge about ML or resource requirements. Therefore, the processes of ML adoption, development, and use in these contexts might exhibit different dynamics when a significant share of ML technology and organization are sourced from or rely on third parties. This issue becomes increasingly important with the proliferation of foundation models, which are often developed by only a handful of firms and used “as-is” or fine-tuned by other organizations (Bommasani et al., 2022). With the externalization of a significant share of cycles that need to be aligned, if MLbC is to be created, there is a risk that the temporal complexity of MLbC increases. This can make, for example, synchronization efforts more challenging. For example, an in-house team developing an ML-based solution for a specific task within a firm and relying on a model provided by a third party through an API (Application Programming Interface) might not be aware of the timings and types of changes that affect the underlying ML algorithm. Another aspect of these developments is the potential for commoditization of MLbC. Organizations which choose to externalize a meaningful share of their MLbC development process run the risk of competitors replicating such capability, thus negating the potential benefits. Therefore, we need to understand how organizations can successfully develop and maintain capabilities when they do not control a significant share of the cycles that are required for MLbC. On the other hand, this question invites an investigation of how firms can bundle together such commoditized MLbC in the form of products or services to create their own unique MLbC. This question is particularly important for organizations that do not score high on digital intensity.

Next, with the increasing sophistication of organizations and maturing of ML technology there is a growing trend of reusing and (re)combining multiple ML systems (Rutschi et al., 2023). Changes in the operating environment or application domain for such multi-ML systems might require different responses than the reframing of a single ML system. This is because multiple ML systems might interact with each other (Lyytinen et al., 2020; Rutschi et al., 2023) and create new dynamics. For example, a large language model (LLM) can be used for generating training data sets for another ML system. A reframing might be needed in that latter system, yet LLM reframing might be delayed or out of control. Particularly in reframing processes which pertain to multiple interlinked ML systems, there might be unexpected emergent behaviors posing risks to either users or system developers. Therefore, the notion of nested or cumulative reframing of several interlinked ML systems presents an increasingly important and timely topic for future investigation. Furthermore, this notion indicates that with the increasing complexity and interrelatedness of ML systems balancing control and efficiency of data work might become particularly challenging.

Overall, this research has concentrated on phenomena unfolding in the vicinity of the technology innovation frontier. Being at the frontier gives a lot of opportunities for spotting new and interesting phenomena, mechanisms, as well as patterns of action-outcome pairs. However, it inescapably means that changes and developments in the underlying phenomena might render new facets of the research problem more relevant or persistent. Therefore, future research on ML in organizations stands to bring much-needed insights.
References


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