

Enacting Large Language Models at Work: Insights for Designing Effective Organizational Training Strategies

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Abstract

Organizations often struggle to integrate new digital technologies into everyday work because adoption is shaped not only by technical features but also by routines, roles, and coordination practices. The rapid diffusion of generative artificial intelligence, exemplified by systems such as ChatGPT and Microsoft Copilot, has intensified this challenge while empirical knowledge about its everyday organizational use remains limited. This thesis examined how knowledge workers enact generative AI within work routines and how these enactments and routines evolve over time. Drawing on the practice lens and sociomateriality, the study conceptualized adoption as an ongoing process in which human action and technology co-constitute technology-in-practice. A qualitative longitudinal design was employed in a small German company in electronics manufacturing. Data was collected through two rounds of in-person shadowing and follow-up semi-structured interviews with seven employees across multiple functions. The analysis identified four themes: generative AI enacted as a flexible collaborator for bounded cognitive tasks, reconfiguration of the human-AI division of labor, the emergence and stabilization of prompting and feature routines, and sociomaterial tensions around trust, control, and risk. Overall, generative AI became embedded through layered workflows in which humans framed tasks, delegated execution, and reclaimed control for validation and refinement. The findings suggest that understanding integration requires practice-based perspectives that capture evolving routines, conditional trust, and shifting agency.

Executive Summary

What was the problem?

Organizations are currently investing heavily in generative AI, yet many struggle to generate tangible value from these investments. The core challenge is practical rather than purely technical. Decision makers often lack clear insight into how employees actually integrate generative AI into their daily work, leaving them unsure of where it helps, where it fails, and what governance and skills are required to integrate it safely. At the same time, established Information Systems adoption models provide limited guidance, as they tend to treat adoption as a one-time event or assume technologies have stable, pre-defined functions. Generative AI is fundamentally different because its outputs are probabilistic, its value emerges through experimentation, and its effective use depends on how knowledge workers enact it in practice.

What was the research methodology?

To address this gap, this thesis applied a qualitative, longitudinal study to examine how knowledge workers integrate generative AI into work routines and how these practices evolve over time. The study took place in a German electronics manufacturing company at an early integration phase of generative AI during data collection, focusing on seven knowledge workers across sales, controlling, marketing, engineering, and management assistance. Between early June and mid-August 2025, the researcher collected empirical material through two rounds of in-person shadowing combined with semi-structured interviews, totaling fourteen hours of observations and approximately 4 hours of interview data. The analysis centered on work routines as the bedrock of organizational practice, investigating how they evolve when new technology is introduced. Guided by a sociomaterial and practice-based lens, the study examined real-world enactments to understand how employees actively configure and shape AI integration through their daily tasks. The data tracked how micro-practices, such as prompting or validation measures as well as routine configurations stabilized or changed over several weeks. This provided a detailed view of adoption as an ongoing process of mutual adaptation between humans and technology, providing implications for how everyday work is reshaped through AI integration.

What were the main findings?

The study identified that the enactment of generative AI is usually integrated in a layered workflow pattern termed the Sandwich Model, where humans provide the initial framing, the AI generates a draft, and humans return to rigorously validate and refine the final output. This configuration signals a fundamental role shift for employees, transforming them from sole creators into supervisors of a capable but fallible assistant. Within this new role, participants often viewed the technology as a flexible collaborator or junior partner rather than a static tool, frequently engaging in conversational prompting to manage tasks like research and content creation. A key finding was the Volatile Boundary of Agency, meaning that delegation was never fully settled. Users would constantly reclaim control from the AI during enactments, whenever they encountered reliability issues such as hallucinations or formatting failures. Over time these practices evolved from exploratory trial-and-error toward stabilized scripts, such as the use of reusable prompt templates and strategic task pre-structuring, indicating that effective integration materializes or increases after an initial experimentation period. Additionally, the study highlighted a distinct trade-off between operational benefits and organizational risks. On one hand, participants reported substantial efficiency gains and higher output quality, as the technology enabled them to produce more varied and polished content or enabled additional steps. On the other hand, this integration introduced sociomaterial tensions and potential risks to the organization. Tasks were absorbed into a self-contained human-AI loop, which leads to a consolidation of human coordination. While this may increase individual speed and efficiency, it risks bypassing valuable social learning and mentorship opportunities. Additionally, the study identified the risk of an Illusion of Competence, where

the AI's ability to generate highly plausible outputs allows employees to appear expert in areas they lack understanding, creating a danger of uncritical acceptance without robust verification.

What should decision makers do?

To harness the efficiency gains of the technology while mitigating risks, leaders must move beyond passive adoption and actively shape the integration process. The following recommendations provide a roadmap for effective governance:

1. **Design workflows around the Sandwich Model.** Operationalize the observed pattern by translating the abstract sequence of human framing, AI execution, and human validation into explicit, enforceable workflow steps. This can be achieved by introducing process checklists and templates for recurring tasks that specify exactly what contextual inputs are required, what the system is expected to produce, and most critically what verification actions are mandatory before any output is used. Support this by defining a task-risk taxonomy that clearly distinguishes between low-risk tasks suitable for delegation and high-stakes activities that must remain human-led.
2. **Invest in practice-oriented training for prompting and verification.** Shift from general awareness to practice-oriented training that builds specific proficiency in prompting and validation. Since employees currently learn primarily through trial-and-error, implement structured training programs to teach concrete skills, such as how to specify roles and constraints, use stepwise prompting approaches, or cross-compare sources. Treat verification as a mandatory part of the workflow and support it with suitable tools where possible.
3. **Institutionalize collective learning through shared resources and peer exchange.** Create and govern shared prompt libraries where effective templates are stored, versioned, and refined to prevent individual reinvention. Complement this with regular roundtables where key users from different departments can exchange insights into their practices and use cases. This combination of digital repositories and social interaction accelerates learning, reduces trial-and-error, and ensures that evolving best practices are effectively disseminated throughout the organization.
4. **Embed data privacy and risk rules into everyday use.** Integrate data privacy rules directly into everyday enactment through standardized prompt starters, default settings, or warning messages that remind users of data constraints in real-time. Define clearly what data is permissible in prompts and provide secure internal models or protected environments where sensitive data can be processed. This reduces the gap between formal policy and routine performance.
5. **Protect organizational learning and reduce the Illusion of Competence.** Actively monitor how AI reshapes social coordination to prevent the isolation of knowledge work. Counteract unintended insulation by creating joint review rituals for AI-supported outputs and intentionally pairing less experienced employees with senior colleagues for validation tasks. Foster a culture of transparency that requires employees to explicitly disclose AI use and articulate the reasoning behind AI-assisted decisions to reinforce accountability.

Ultimately, successful integration depends less on the technology itself and more on the disciplined practices that govern its use. By treating generative AI as a supervised collaborator within these clear boundaries, organizations can leverage its productivity potential without compromising on accuracy or accountability.

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1. Introduction

Organizations have long faced challenges in adopting new technologies. While new tools promise efficiency gains and new ways of working, their successful integration into everyday organizational practices often proves difficult. Adoption is not only a technical matter but also a social and organizational one, as new technologies interact with existing work practices, roles, and infrastructure. Understanding how technologies are taken up in practice therefore remains a central concern for both organizations and for researchers. Generative artificial intelligence represents a particularly salient recent case of this challenge. Initiated by the release of OpenAI's ChatGPT in late 2022, a new era of artificial intelligence with a promise of tremendous efficiency gains was introduced. Generative AI systems able to produce text, images, code and other media, ever since have diffused at an unprecedented pace, surpassing the adoption curves of personal computers and the internet (Bick et al., 2024; Rosen, 2023). Organizations rapidly joined this wave, with executives recognizing generative AI as a transformative force and prioritizing its implementation in their strategic agendas (Brown, 2025; Deloitte, 2025; Scott, 2025).

Yet despite this enthusiasm, organizations struggle with implementation. How such systems can be integrated into everyday organizational work remains poorly understood. Companies lack empirical knowledge of how employees actually use generative AI in practice, what tasks they are applied to, how workflows adapt, and what risks or inefficiencies emerge in daily practice (Deloitte, 2025). Without such understanding, organizations risk underutilization, compliance breaches, or misaligned governance.

This gap is mirrored in academia. Traditional adoption models such as TAM, UTAUT, or TOE explain initial acceptance well, but focus on short-term intention and assume stable technologies (Baker, 2012; Davis & Granić, 2024; Venkatesh et al., 2003). These models have been applied across diverse technological contexts, from enterprise resource planning (ERP) systems and mobile applications to collaborative platforms and e-commerce solutions (e.g., Lee et al., 2003; Venkatesh et al., 2012). This breadth illustrates the robustness of these frameworks in explaining IT adoption across domains, yet they primarily address stable technologies with predefined functionalities and outputs.

Prior AI-at-work studies similarly examined narrow, deterministic systems, which often performed classification or prediction tasks and generated bounded output such as labels or probability scores. These systems were mainly specialized in pattern recognition and were built on explicit rules or narrow models tailored to specific tasks like image classification or fraud detection (Burton-Jones & Grange, 2013; Felten et al., 2023; Wessel et al., 2025).

Adoption models and prior studies therefore rest on assumptions of stability and determinism. These assumptions do not hold for generative AI. This technology is open-ended, its use cases often emerge through experimentation, its outputs continually reshape tasks, and it resembles a collaborator rather than a fixed tool (Anthony et al., 2023; Zhang et al., 2023). Yet little is known about how people collaborate with such systems (Anthony et al., 2023; Hafermalz & Seymour, 2016) and information system (IS) research has often overlooked everyday interaction experiences (Yoo, 2010). Scholars therefore argue that generative AI challenges foundational assumptions in IS and necessitates new theories, methods, and models (Anthony et al., 2023; Dwivedi et al., 2023).

In sum, this presents a clear research gap: organizations lack empirical knowledge of how generative AI becomes integrated into everyday work, including what tasks it supports and how it shapes work practices in use. Meanwhile, existing research offers limited guidance because insights derived from earlier technologies cannot be readily generalized to generative AI, given its emergent, non-deterministic outputs and deep entanglement with human practices. Addressing the practical challenge of implementation therefore requires addressing the academic one, by moving beyond models that conceptualize adoption as a one-off event towards an understanding of adoption as an ongoing process of mutual adaptation between humans and technology.

This thesis responds to this gap by focusing on the early-phase integration of generative AI into organizational work and examining how it is enacted in everyday routines. Rather than assessing adoption outcomes or usage intentions, the study concentrates on how generative AI is taken up, experimented with, and stabilized through day-to-day work practices. This focus allows the investigation of adoption as it unfolds in practice and captures how human action and technology co-evolve over time.

To address this, the study draws on two theoretical perspectives: Orlikowski's (2000) practice lens and sociomateriality (Orlikowski, 2007). The practice lens views technology not as a fixed tool. Instead, technology is enacted, meaning it comes into being through people's situated use in day-to-day work. While a sociomaterial lens conceptualizes human action and technology as inseparably intertwined. These perspectives are particularly relevant for generative AI, as they highlight the mutual shaping of technology and human practice. The results of generative AI depend on how humans instruct it, and its flexible applications means that it is not a fixed technology with predefined use cases, hence the practice lens and sociomateriality are necessary to capture this mutual constitution.

Work routines provide the empirical context. As indicators of organizational practices, their dynamics offer valuable insight into how new technologies influence work. The objective of the study is therefore to examine how the introduction of generative AI affects organizational work practices by empirically investigating its enactment within routines.

The study explores how knowledge workers engage with generative AI in their routines and how these enactments evolve over time. It further investigates how generative AI integration reshapes the routines themselves. To capture this, the analysis focuses on micro-level performances, such as prompting, validation, and collaboration, through which AI becomes embedded in work. These performances serve as the unit of analysis, enabling the observation of enactments and providing a basis for assessing their broader organizational implications.

The study is guided by the following research questions:

How do knowledge workers enact generative AI in their work routines and how do these enactments and routines evolve over time?

Sub-questions:

- ***SQ1:*** *What use cases of generative AI can be identified in organizational work contexts and how are work routines defined?*
- ***SQ2:*** *How do knowledge workers enact generative AI within their work routines?*
- ***SQ3:*** *How do enactment practices of generative AI and work routines evolve over time?*

To answer these questions, the study adopts a qualitative, longitudinal design. Data is collected through observations and semi-structured interviews in an organization currently introducing generative AI to its workforce. This site is well-suited as it allows observation of enactments as they emerge in real-time and provides access to early adoption practices and their evolution. The longitudinal design and data collection method directly addresses the lack of empirical knowledge on everyday integration by capturing actual enactments and their development as they unfold.

The study makes two key contributions. Theoretically, it extends IS research by offering an empirically grounded account of how generative AI is enacted and becomes embedded in work routines, interpreted through a sociomaterial lens. This is relevant because it provides rare empirical insights into a technology that challenges existing theories, thus helping scholars refine and adapt models of technology integration for this novel technology. Practically, it provides organizations with insights into how

generative AI affects everyday work, highlighting both opportunities for efficiency gains and areas where training, governance, or support structures are required.

To address how knowledge workers enact generative AI in their routines and how these enactments and routines evolve over time, the study must first establish its theoretical foundation. This foundation clarifies how the phenomenon is conceptualized and why a practice-oriented, sociomaterial perspective is required. As discussed above, the effective integration of generative AI into organizational work depends on rethinking technology adoption as an ongoing, co-evolutionary process between human and AI. The following chapter therefore develops the theoretical framework that enables this shift in perspective.

2. Theoretical Background

The previous chapter identified the research problem and highlighted the need for a different perspective on the introduction of technologies. This chapter now presents the theoretical foundations that enable such a different perspective. The goal of this chapter is to clarify the analytical lens that guides this study and specify the key concepts underpinning the subsequent empirical analysis.

To this end, the chapter is divided into two main sections. In the first section, the most important concepts are briefly explained and, building on this, the framework that connects these concepts and guides this study as the investigative lens is presented. In the second section, the theoretical concepts are examined in more detail. As such, insights from the practice lens, sociomateriality and routine theory are presented, to depict the mutual shaping of technology, humans and work practices. In addition, generative AI is being investigated as a technology. Particular focus is placed on its capabilities and use cases in business, but also on limitations and ways to mitigate them. These insights lay the foundation for the subsequent data collection and analysis.

2.1. Conceptualization

The purpose of this section is to clarify the analytical lens that guides this study and specify the key concepts underpinning the empirical analysis. It briefly presents the main concepts relevant to the study: enactment of generative AI, work routines and sociomateriality and integrates these concepts into a comprehensive conceptual framework, which will serve as the investigative lens of the empirical research that follows.

2.1.1. Enactment of Generative AI

Enactment refers to how people actively shape how generative AI is used in their day-to-day work through situated practice and thereby form the technology-in-practice. Instead of viewing the technology as a passive tool that is adopted, following (Orlikowski, 2000) “practice lens”, it is perceived as something that emerges in practice as people experiment, improvise, adjust and refine how they use it. This perspective shifts attention away from questions of adoption or simple tool use toward the situated and practical ways employees make AI useful, which can be made visible through micro-practices such as prompting, validation and collaboration.

2.1.2. Work Routines

In this study, work routines are defined as dynamic, repetitive, and recognizable patterns of interdependent actions, collaboratively enacted by multiple actors, forming the bedrock of organizational work practice (Feldman, 2000; Feldman & Pentland, 2003; Howard-Grenville, 2005). They are characterized by an inherent dynamic which enables endogenous change to the routine and as such organizational work practice (Becker, 2004; D’Adderio, 2008; Feldman & Pentland, 2003; Howard-Grenville, 2005). This change is driven by technological artifacts, such as generative AI, which can actively shape how routines evolve by creating new affordances or constraining actions, thereby reframing existing patterns (D’Adderio, 2008; Glaser, 2017; Leonardi, 2011). Further, individual performances of work routines lead to change through reflections, variation and continuous adjustment (Feldman & Pentland, 2003; Howard-Grenville, 2005).

These performances are the context where the enactment of the technology-in-practice can be observed, revealing the ongoing and emergent ways in which technology is enacted and mutually shapes work practices. Therefore, individual performances within work routines will serve as the unit of analysis to observe the enactment practices. The analytical focus is on how these performances are configured with regards to the integration of generative AI or task division, and how this configuration behaves over time, tracing stabilizing, but also emerging or disappearing aspects.

2.1.3. Sociomateriality

To analyze these practices, the study adopts sociomateriality as its guiding theoretical lens. Sociomateriality emphasizes that human and technological elements are not separate but are always intertwined in practice so one cannot fully be understood without the other (Orlikowski, 2007). This perspective enables the link between everyday enactment to organizational change, by tracing how agency shifts between technology and human. Sometimes people guide the task with their choices and skills, other times the tool's features and limits guide the next action. By paying attention to these agency shifts as well as to what the technology enables (affordances) or blocks (constraints), it can be seen how daily practices and routines are performed, adjusted and sometimes rebuilt over time (Leonardi, 2011).

2.1.4. Conceptual Framework

This study conceptualizes enactment practices of generative AI as situated within individual routine performances that instantiate broader work routines. Using a sociomaterial lens, it treats human action and AI capacities as inseparably entangled in practice. Enactment micro practices shape individual routine performances, such as workflow changes and allow theorized implications for routine reconfiguration over time. In sum, routines provide the context, enactment represents the object of study, and sociomateriality serves as the analytical lens for understanding their interplay.

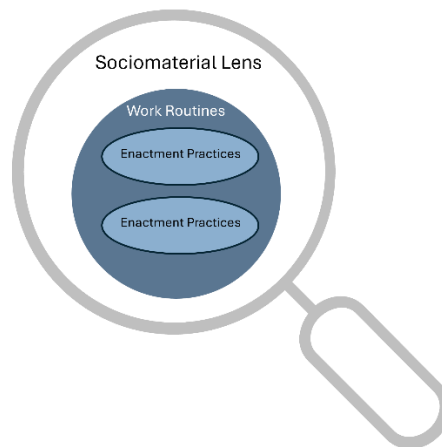


Figure 2.1: Visualization of Conceptual Framework

2.2. From Adoption to Enactment: Theoretical Perspectives on Technology Use

This chapter introduces the theoretical perspectives that frame how technologies become integrated into organizational work. It begins by revisiting established technology adoption models to acknowledge their contributions and to clarify their limitations when applied to generative AI. These limitations motivate a shift toward practice based and sociomaterial perspectives, which conceptualize technology use not as a one-time adoption decision but as an ongoing process enacted through everyday work. Together, these perspectives establish the theoretical lens through which this study examines how generative AI and human actors co-constitute enactment and organizational routines.

2.2.1. Traditional Models and Limitations

Traditional technology adoption models are often anchored in the Technology Acceptance Model (TAM), which posits that perceived usefulness and perceived ease of use shape attitudes, intentions and subsequent use for a technology (Davis & Granić, 2024). Extensions of the model retain this core while broadening the factors. For instance, TAM2 incorporates social influence and cognitive instrumental processes (Venkatesh et al., 2003), and TAM3 adds determinants of ease of use and experience effects (Venkatesh & Bala, 2008). Other approaches include hybrid and integrative formulations such as C-TAM-TPD, which joins TAM with the Theory of Planned Behavior (Taylor & Todd, 1995), and the Unified Theory of Acceptance and Use of Technology (UTAUT), which synthesizes eight streams into performance/effort expectancy, social influence and facilitating conditions (Venkatesh et al., 2003), with UTAUT2 adapting these to consumer settings (Venkatesh et al., 2012). At the organizational level, adoption is often framed via the Technology–Organization–Environment (TOE) lens (Baker, 2012).

These models are robust for predicting initial acceptance and user responses to technology. However, for assessing the adoption of generative AI they are poorly suited. First, they focus on intention and short-term use as proxies for adoption, but neglect the longer processes of assimilation, routinization and adaptation that are critical for technologies whose value emerges only through ongoing interaction. This is an important limitation for generative AI, which is inherently open ended. Its use cases are not pre-specified but discovered through experimentation, learning and adjustment. Over time, as users refine prompts and workflows, the system has the ability to adapt to specific contexts and user behavior and may even increase in value rather than stabilizing. This requires a perspective that accounts for the evolving nature of adoption.

Second, traditional models assume technologies are stable artefacts with a fixed set of features. This assumption breaks down for generative AI, which produces novel outputs in response to user input and continuously reshapes how tasks are carried out. Treating such systems as tools that are simply used underestimates their role. Generative AI suggests the next steps, engages in dialogue in natural language, and in many ways resembles a collaborator rather than a passive instrument.

2.2.2. Practice Lens and Sociomaterial Perspective

Understanding the integration and impact of a new technology such as generative AI requires a theoretical approach that moves beyond traditional views of technology as a passive tool which is adopted once. Generative AI distinguishes itself from other technologies by mimicking human cognitive abilities, creating unique and creative content and performing strategic tasks - domains that were historically considered uniquely human. Thus, perspectives viewing technology as passive tools are no longer suitable for understanding generative AI and researchers are increasingly recognizing the need for a research approach that identifies AI as an active participant in interactions and a “counterpart” in work practices (Drossel & Löfgren Hallbeck, 2024).

One suitable perspective is the concept of sociomateriality and the practice lens. Sociomateriality, by emphasizing the inherent inseparability and constitutive entanglement of the social and the material, offers a perspective to understand how humans and generative AI are collaborating to achieve a task.

The practice lens is a foundational theoretical approach to studying technology in organizations. It shifts the analytical focus from assumptions about structures being embedded within technologies to emergent structures that arise in practice (Orlikowski, 2000). Instead of starting with the technology’s design features and asking how users adopt or appropriate them, this perspective starts with human action and examines how people, through recurrent interaction with technology, enact new structures and ways of working (Orlikowski, 2000, 2002).

These enacted, emergent structures are referred to as technology-in-practice. Crucially, these structures are not fixed or inherent in the technology itself but rather emerge from the ongoing and situated interactions users have with it. Over time, these enacted technologies-in-practice can become routinized within an organization (Orlikowski, 2000).

Enactment is the process by which these technologies-in-practice are formed. Rather than viewing technology use as simply appropriating predefined structures embedded in a technology, enactment emphasizes how human action actively constitutes emergent structures through recurrent interaction with the technology at hand. This means users can ignore, work around or invent new ways of using the technology, thereby opening possibilities for innovation, learning and change. For example, many of us use software like word processors or spreadsheets in a highly limited way, leveraging only 25% of the functionality we actually need and ignoring the rest (Orlikowski, 2000).

Finally, sociomateriality provides the broader overarching theoretical framework and posits an inherent inseparability between the technical and the social, saying that “*there is no social that is not also material, and no material that is not also social*” (Orlikowski, 2007). It shifts analysis to how this entanglement of the social and the material is enacted in everyday practice and with what consequences (Leonardi, 2013; Orlikowski, 2007; Orlikowski & Scott, 2008).

Within this lens, agency is not a fixed property of humans or technology but an ongoing process in practice. Human agency entails goal formulation and purposive action, while material agency appears as performativity or what technologies do in operation (e.g. compiling, suggestions, calculations). These agencies interdepend and co-emerge in use. Their intertwining produces, sustains or alters routines and artefacts over time and is path dependent, meaning past interactions influence future ones (Leonardi, 2011, 2013; Orlikowski, 2007).

Another important aspect of this lens refers to affordances, which denote the possibilities for action coming from the actor’s goals and the technological capabilities, not from either alone. Perceived affordances typically precipitate change in routines, as new possibilities are taken up, whereas perceived constraints often prompt changes in the technology or its configuration (Leonardi, 2011).

Taken together, these perspectives demonstrate why traditional adoption models are insufficient for studying generative AI. A practice based and sociomaterial lens instead allows analysis of how generative AI is enacted in everyday work and how its use evolves through interaction with human actors. This theoretical framing establishes the basis for examining the concrete organizational contexts in which such enactments unfold, which are addressed through the concept of work routines in the following section.

2.3. Work Routines: Foundations of Organizational Practice

Having established enactment and sociomateriality as the overarching theoretical lens, the analysis now turns to the organizational context in which enactments of generative AI take place. Work routines provide a concrete and observable setting for examining how human actors and technologies co produce organizational practice. By reviewing how routines are defined, how they are performed and how they change over time, this section situates individual performances as the micro level sites where generative AI becomes embedded and where organizational change can be observed.

2.3.1. Definition and Role of Routines within Organizations

Organizational routines are fundamentally defined as repetitive, recognizable patterns of interdependent actions carried out by multiple actors (Feldman & Pentland, 2003). This definition highlights several key characteristics: routines consist of multiple steps or actions that are interdependent (each action is connected to others in sequence or purpose), they are recognizable (people can identify the pattern as a distinct routine) and often involve multiple participants working together. An example of this can be the

monthly reporting in a company. It involves multiple steps, such as gathering the data, analyzing it, writing a report, reviewing and approving, which are carried out by different people but together form a coherent and repeatable process. They differ from general tasks or processes. While tasks are specific actions or objectives, and processes are broader sequences of activities, routines represent a particular kind of patterned process - the "how" of accomplishing organizational work through established, though not necessarily rigid, sequences of interaction (Feldman, 2000; Feldman & Pentland, 2003).

Furthermore, routines are understood through two interconnected aspects: the ostensive and the performative. The ostensive aspect refers to the abstract, general idea or pattern of the routine - the version that people describe, follow or use to explain specific actions. The performative aspect, on the other hand, consists of the specific actions taken by particular individuals, at specific times and places that bring the routine to life (Feldman & Pentland, 2003; Pentland & Feldman, 2005). These concrete performances can deviate from the ostensive script while still being recognizable as the routine. (Feldman & Pentland, 2003) describe it as follows: "*The ostensive aspect of the routine is the idea; the performative aspect, the enactment.*"

Routines serve as the foundation of work practices within organizations, underpinning much of what organizations do and how they function. Thus, they are considered crucial for understanding various organizational phenomena. This role of routines for organizational work practices can be explained through several mechanisms. They give organizations structure and efficiency, saving time and mental effort by providing ready-made steps for recurring tasks (Becker, 2004). In addition, routines facilitate coordination among members by making activities consistent and predictable, providing people a sense of what others will do (Becker, 2004). Also, they serve as an organizational memory, storing both explicit and tacit knowledge about how work is done. In doing so they persevere knowledge across individuals and teams, enable learning and form the building block of organizational capabilities (Becker, 2004; Feldman & Pentland, 2003).

2.3.2. Routine Dynamics

Routine dynamics is a field that emphasizes the internal working and ongoing processes of organizational routines. It perceives them as generative and dynamic systems that contribute to both stability and change. This perspective moves beyond the traditional idea of routines as fixed, unchanging objects and highlights their constant evolution through an "*internal dynamic*" that can promote continuous change (Feldman, 2000; Feldman et al., 2016; Feldman & Pentland, 2003; Pentland & Feldman, 2005).

A primary engine of this change are the individual performances within routines, which constitute the "*performative aspect*" or the actual enactments of routines (Feldman & Pentland, 2003; Pentland & Feldman, 2005). These performances are not mindless repetition but "*effortful*" and "*emergent accomplishments*" (Feldman, 2000), involving individual agency, choice and improvisation. Each time an individual performs a routine, reflects and responds to the outcomes, they introduce variations, learn and as a consequence adapt the next iteration. These variations can accumulate over time and drive change within the routine itself (Becker, 2004; Feldman, 2000; Feldman et al., 2016; Feldman & Pentland, 2003; Pentland & Feldman, 2005).

Another important driver of change within organizational routines is technology. Technological artifacts, not only support but also mediate individual performances, thereby shaping how routines evolve over time (D'Adderio, 2008; Pentland & Feldman, 2005). Even seemingly minor modifications can have significant consequences. For example, when the report format in a marketing decision-making routine shifts from paper to electronic form, new possibilities emerge. Electronic documents enable functions like automated search, which alter how facts are accessed and compared. Such changes reconfigure patterns of interaction and task execution, ultimately transforming the routine itself (Becker, 2004).

This example demonstrates that the introduction of new technologies is not a passive event but triggers an active, iterative process of adaptation and change within organizational routines. Technologies in this case are not merely passive tools. They exert their own “material agency”, making certain actions possible or easier, while making others impossible (D’Adderio, 2008; Leonardi, 2011).

These mechanisms operate within “*sociomaterial assemblages*” where human and material agencies are imbricated, or interlocked in particular sequences that produce, sustain or change routines and technologies (D’Adderio, 2008; Glaser, 2017; Glaser et al., 2021; Leonardi, 2011). This interplay between human agency and the enabling or constraining elements of technology means that routines are constantly in flux, with individual actions and technological capabilities mutually shaping their ongoing evolution (Feldman & Pentland, 2003; Leonardi, 2011; Pentland & Feldman, 2005).

This discussion highlights that work routines constitute the stage on which enactments unfold. In particular, the performative aspect of routines reveals how technologies are enacted in practice. Individual performances are shown to be a key driver of routine change, as small deviations introduced through the interaction of human agency and technology may accumulate into broader reconfigurations. This underscores the importance of examining micro level sites of action when studying how new technologies become embedded in organizational work. To understand these enactments in context, the following section turns to the specific characteristics, capabilities and limitations of the technology under investigation: generative AI.

2.4. Generative AI in Organizational Contexts: Capabilities, Challenges and Use Cases

To connect the preceding theoretical discussion with the characteristics of the technology under investigation, this section examines generative AI in more detail. It reviews the core capabilities that distinguish generative AI from earlier forms of artificial intelligence and outlines current business use cases. It further discusses key limitations and risks that shape how people interact with generative AI in practice. Understanding these technological characteristics provides the basis for targeted data collection and analysis in the empirical part of the study.

2.4.1. Defining and Distinguishing Generative AI

Generative AI refers to AI systems that can produce novel content (text, images, code, etc.) in response to a query or prompt (Deloitte, 2025; Feuerriegel et al., 2023; Fui-Hoon Nah et al., 2023; Yang et al., 2024). These systems use algorithms to create new data by drawing upon patterns and relationships observed in their training data. Thereby, they can predict the next element in a sequence of words. A key characteristic is their ability to produce content that is often indistinguishable from humans (Burtsev et al., 2024; Feuerriegel et al., 2023). Large Language Models (LLMs) are a prominent example of generative AI, forming the basis of systems like ChatGPT (Brynjolfsson et al., 2023; Minaee et al., 2025).

Compared to previous forms of AI, often referred to as discriminative, traditional or analytical AI, generative AI shows a few fundamental differences. Previous AI applications were often designed for specific tasks like classification or pattern recognition, relying on explicit programming or structured training data for each use. They focused on automation, prediction and accuracy in well-defined domains. By contrast, generative AI excels at creating new output such as news articles or software that may be indistinguishable from human work (Brynjolfsson et al., 2023; Felten et al., 2023; McAfee et al., 2023; Retkowsky et al., 2024; Wessel et al., 2025; Yang et al., 2024). In addition, generative AI is not explicitly instructed for a certain application or task. Instead, it generalizes through learned statistical patterns from its training data, which significantly expands the possibility for applications and makes it a multi-purpose technology (Brynjolfsson et al., 2023).

2.4.2. Capabilities and Business Use Cases of Generative AI

Generative AI, including Large Language Models (LLMs) shows some impressive capabilities, which can offer significant business advantages if leveraged across various domains. In the following four capabilities of generative AI as well as potential business use cases for each are presented. While the landscape of generative AI continues to evolve rapidly and new applications are constantly emerging, the following categories reflect relevant and observable use cases at present. They serve as analytical anchors rather than a taxonomy and inform the study's data collection and coding scheme by informing observational focus points and a classification of enactment practices.

Natural Language Understanding and Processing

LLMs are proficient in comprehending and interpreting human language, enabling a range of applications. For businesses, this enables e.g. conversational agents and chatbots that can assist customers or provide real time suggestions for human agents (Brynjolfsson et al., 2023; Deloitte, 2025; Fui-Hoon Nah et al., 2023). These can be used both for internal purposes such as sales teams accessing internal knowledge and for external customer-facing interactions. Furthermore, LLMs show the ability to follow instructions for tasks without explicit examples, which means they can assist with a myriad of business-related tasks based on natural language commands (Deloitte, 2025; Minaee et al., 2025). All of this can be done across multiple languages, offering advanced possibilities to global businesses (Grattafiori et al., 2024; Laskar et al., 2024).

Content Generation

A primary capability of generative AI is its ability to create novel and meaningful content that is often indistinguishable from human work. In a business context, this includes text generation for diverse purposes, such as crafting marketing slogans, emails or job requisitions. For developers, generative AI excels at code generation, producing entire code snippets, unit tests with mock data, SQL commands as well as debugging and explaining code, significantly boosting productivity (Brachman et al., 2024; Brynjolfsson et al., 2023; Feuerriegel et al., 2023; Grattafiori et al., 2024; McAfee et al., 2023; Minaee et al., 2025; Retkowsky et al., 2024). Beyond text generation, these models can also perform image and video generation, creating artwork or marketing images and videos from prompts (Deloitte, 2025; McAfee et al., 2023; Yang et al., 2024).

Information Retrieval and Knowledge-intensive tasks

Generative AI systems can access, process and summarize vast amounts of information. Businesses can leverage this for intelligent question-answering, where models act as sophisticated search engines to answer both general and domain specific questions, with the ability to retrieve information from internal and external knowledge sources (Brachman et al., 2024; Minaee et al., 2025; Retkowsky et al., 2024; Yang et al., 2024). Solutions like ChatPDF exemplify this by delivering answers with references from uploaded PDF documents (Yang et al., 2024). In addition, the summarization capabilities of the models allow for concise descriptions of lengthy content such as marketing reports or meeting transcripts (Brachman et al., 2024; Feuerriegel et al., 2023; Retkowsky et al., 2024). For data analysis, this can be used to uncover new insights from information and data and even explain the logic of complex business analytics models intuitively for non-experts (Brachman et al., 2024; Deloitte, 2025; Feuerriegel et al., 2023). It can also be applied to market research and can drastically improve knowledge retrieval with techniques like Retrieval-Augmented Generation (RAG), which enhances accuracy by incorporating external knowledge sources (Brachman et al., 2024; Brynjolfsson et al., 2023; Grattafiori et al., 2024; Laskar et al., 2024; Minaee et al., 2025).

Reasoning and Problem Solving

Another core capability of generative AI is the ability to generalize and provide answers when facing out of distribution data, enabling emergent problem-solving abilities. Paired with multi-step reasoning

and logical deduction, this translates into the capacity for complex problem-solving for businesses (DeepSeek-AI et al., 2025; Grattafiori et al., 2024; Minaee et al., 2025; Yang et al., 2024). Thus, generative AI can assist with strategic assessment and decision making by creating business case analyses or aiding in decision analysis (Brynjolfsson et al., 2023; Feuerriegel et al., 2023). Further, in business process management it can generate process descriptions or support innovative process design initiatives or it can assist with debugging and validation – checking if code or documents satisfy specific requirements (Brachman et al., 2024; Feuerriegel et al., 2023). Additionally, the more recent emergence of autonomous AI agents signifies a major advancement, by allowing these systems to complete complex tasks and meet objectives with little or no human intervention, planning and executing actions, using various tools and coordinating with other AI agents. These agents can be specialized for certain functions and take over certain tasks like e.g. sales research (Deloitte, 2025; Feuerriegel et al., 2023; Minaee et al., 2025).

Table 1 summarizes prominent business use cases for generative AI, including examples. The business use cases are mapped to the above discussed core capabilities.

Table 1: Business Use Case, Examples and Core Capabilities

Business Use Case	Examples	Core Capabilities
Content Creation & Enhancement	Marketing copy, business documents, customer communications, technical manuals, product descriptions, proposals, contracts, presentations, newsletters (Brachman et al., 2024; Deloitte, 2023b; Feuerriegel et al., 2023).	Content Generation
Ideation & Brainstorming	Idea generation for R&D, design, slogans, product development, strategy; automated brainstorming in innovation and team settings (Brachman et al., 2024; Deloitte, 2023b; McAfee et al., 2023; Retkowsky et al., 2024).	Content Generation, Reasoning & Problem Solving
Customer Service & Engagement	AI-powered chatbots, automated response generation, onboarding guidance, help desks, personalized recommendations (Brachman et al., 2024; Brynjolfsson et al., 2023; Deloitte, 2023b; Fui-Hoon Nah et al., 2023).	Natural Language Understanding & Processing, Reasoning & Problem Solving
Knowledge Management & Retrieval	Search/summarization of documents/policies, Q&A bots, extraction from enterprise data (emails, wikis) (Brachman et al., 2024; Feuerriegel et al., 2023; Retkowsky et al., 2024; Yang et al., 2024).	Information Retrieval & Knowledge-intensive Tasks, Natural Language Understanding & Processing
Process Automation & Task Augmentation	Automated scheduling, workflow orchestration, RPA via natural language, form completion, data entry, HR/accounting/procurement automation (Brachman et al., 2024; Brynjolfsson et al., 2023; Deloitte, 2023b; Retkowsky et al., 2024).	Reasoning & Problem Solving, Natural Language Understanding & Processing
Software & Code Generation	Code snippets, scripts, automated documentation/code reviews, code translation (Brachman et al., 2024; Feuerriegel et al., 2023; Yang et al., 2024).	Content Generation, Reasoning & Problem Solving
Decision Support & Analysis	Market research synthesis, competitor analysis, automated business cases/risk assessments, dashboard summaries, forecasting (Brynjolfsson et al., 2023; Deloitte, 2023a; Feuerriegel et al., 2023; McAfee et al., 2023).	Reasoning & Problem Solving, Information Retrieval & Knowledge-intensive Tasks
HR, Training & Learning	Onboarding guides, job descriptions, interview scripts, training material, personalized learning journeys, performance feedback, upskilling content (Brachman et al., 2024; Deloitte, 2023a; Feuerriegel et al., 2023; Retkowsky et al., 2024).	Content Generation, Natural Language Understanding & Processing

Compliance, Risk & Legal Support	Drafting legal/compliance documents, KYC checks, due diligence, fraud detection, regulation summaries, compliance checklists (Deloitte, 2023a; Feuerriegel et al., 2023; McAfee et al., 2023).	Reasoning & Problem Solving, Information Retrieval & Knowledge-intensive Tasks
Multimodal Creative Production	Synthetic images/videos for ads/training, automated translation/subtitles, data visualization, marketing collateral, audio narration (Fui-Hoon Nah et al., 2023; Retkowsky et al., 2024; Yang et al., 2024).	Content Generation

2.4.3. Limitations and Best Practice for Generative AI

Although generative AI shows some remarkable capabilities and use cases, it introduces characteristic risks that directly shape how employees enact the technology (e.g. verification steps, prompt strategies, data-handling practices). In the following several notable limitations of the technology as well as potential mitigation techniques are presented.

Generative AI models, especially LLMs, frequently produce outputs that are factually incorrect, nonsensical or unfaithful to the source input (Brynjolfsson et al., 2023; Feuerriegel et al., 2023; Fui-Hoon Nah et al., 2023; Minaee et al., 2025; Retkowsky et al., 2024; Yang et al., 2024). These so called “hallucinations” arise because models generate the most probable response, not necessarily the correct one, and lack inherent notion of “truth”. The fluent and human-like nature of the output easily masks these errors, making them difficult to verify and distinguish from authentic content (Feuerriegel et al., 2023; Minaee et al., 2025; Yang et al., 2024).

In addition, outputs can contain certain bias, which were present in the training data and get perpetuated by the model. These biases can often be subtle and require subjective interpretation (Feuerriegel et al., 2023; Retkowsky et al., 2024; Yang et al., 2024). Also, models can produce content that resembles or directly copies copyrighted work without permission, potentially causing legal challenges (Feuerriegel et al., 2023; Fui-Hoon Nah et al., 2023; McAfee et al., 2023).

To mitigate these issues, a thorough validation of the generated output is recommended. Thus, it is important to have the human-in-the-loop to carefully check the answers and request references to verify information (Burtsev et al., 2024; Feuerriegel et al., 2023; McAfee et al., 2023). Also, applying advanced prompting techniques like RAG, can help ground models in external verified knowledge to address the risk of hallucinations (Minaee et al., 2025).

Furthermore, despite the emergent abilities for complex problem solving, LLMs lag in complex logical reasoning, often struggling with seemingly simple tasks like verifying prime numbers or inferring familiar relationships from an inverse query. This is because the standard models are often not inherently built for complex logical reasoning (Burtsev et al., 2024). This limitation can be addressed in several ways. First, advanced prompting, such as Chain-of-Thought (CoT) prompting can be used to guide models through systematic reasoning steps. In addition, specialized models for reasoning can be deliberately chosen for problem solving tasks (Burtsev et al., 2024; Minaee et al., 2025; Yang et al., 2024).

Uploading sensitive information such as personal identifiers or trade secrets into external models can lead to data privacy risks, as the input is often used for training purposes (Fui-Hoon Nah et al., 2023; McAfee et al., 2023). A prominent case was a data-leakage of Samsung, where employees used ChatGPT to process their work and inadvertently leaked company source code (Yang et al., 2024). Safety measures include user caution when uploading information, data cleaning to anonymize information or the use of internal “safe” models (Fui-Hoon Nah et al., 2023; McAfee et al., 2023; Yang et al., 2024).

Additionally, LLMs struggle to understand and generate extensive texts due to their limited context windows, which restricts their ability to process long documents or chat histories. This can lead to memory loss and stale information (Minaee et al., 2025; Yang et al., 2024). This needs to be considered when working with the model, to avoid misinformation or contextually irrelevant answers.

Table 2 consolidates the insights presented above and maps prominent challenges and limitations to respective mitigation techniques, which will inform the further investigation.

Table 2: Limitation/Challenge and Mitigation Technique

Limitation / Challenge	Mitigation Technique
<i>Hallucinations</i> : Models generate factually incorrect, nonsensical, or unfaithful outputs, which are hard to distinguish from authentic content.	Human-in-the-loop verification and requesting references to validate information (Burtsev et al., 2024; Feuerriegel et al., 2023; McAfee et al., 2023). Grounding models with external verified knowledge using advanced prompting techniques such as Retrieval-Augmented Generation (RAG) (Minaee et al., 2025).
<i>Bias in outputs</i> : Training data biases are perpetuated by models.	Careful human review and awareness of subjective interpretation to detect bias (Feuerriegel et al., 2023; Retkowsky et al., 2024; Yang et al., 2024).
<i>Copyright concerns</i> : Potential reproduction of copyrighted material without permission.	Verification of originality, monitoring outputs, and adhering to copyright compliance practices (Feuerriegel et al., 2023; Fui-Hoon Nah et al., 2023; McAfee et al., 2023).
<i>Weak logical reasoning</i> : LLMs struggle with complex logical reasoning.	Use advanced prompting techniques such as Chain-of-Thought (CoT) prompting to guide reasoning (Burtsev et al., 2024). Employ specialized reasoning models or tools (Burtsev et al., 2024; Minaee et al., 2025; Yang et al., 2024).
<i>Data privacy risks</i> : Sensitive input (personal identifiers, trade secrets) can be exposed.	Avoid uploading sensitive information; anonymize or clean data; use internal or “safe” models (Fui-Hoon Nah et al., 2023; McAfee et al., 2023; Yang et al., 2024).
<i>Limited context window</i> : Models struggle with long documents or chat histories, leading to memory loss or stale information.	Be mindful of context limitations; chunk long documents; apply strategies to manage input length (Minaee et al., 2025; Yang et al., 2024).

The discussion of capabilities and limitations highlights that generative AI is not a neutral tool but a technology whose material characteristics actively shape enactment in practice. These characteristics influence how routines are performed, adapted and stabilized over time. Together with the preceding theoretical perspectives on enactment and routines, this understanding provides a coherent foundation for the methodological approach adopted in the following chapter, which examines how generative AI is enacted in everyday organizational work.

3. Methodology

After presenting the theoretical foundations and investigative lens in the previous chapter, this chapter dives into the applied methodology. The chapter is divided into three sections. The first section gives an overview of the overall research design that was developed for this study. Followed by a section presenting how the data was collected through interviews and observations, as well as how the theoretical lens was operationalized to inform data collection. Finally, the data analysis process is explained in detail, including how the findings were derived, which are then presented in the subsequent chapter.

3.1. Research Design

This study investigates how knowledge workers enact generative artificial intelligence within their work routines and how these enactments and routines evolve over time. To address this, the study adopts a qualitative, longitudinal, and practice-oriented research design. This design is appropriate because the phenomenon under investigation concerns situated practices, micro level performances, and ongoing change rather than stable variables or discrete adoption decisions.

The empirical setting was a small German company in the electronics manufacturing sector. The organization was selected through prior professional access and provided a suitable research context because it was in an early phase of generative AI integration. To mitigate insider bias, the study distinguished strictly between descriptive observations and interpretive memos. Furthermore, member checking during follow-up interviews was used to confirm that observations aligned with participants' actual experiences, while longitudinal observations reduced the risk that observed behavior was merely displayed for the researcher.

At the time of data collection, organizational guidelines for AI use were already in place, yet concrete enactment practices were still emerging and varied across roles and departments. This situation enabled the observation of how generative AI was taken up, experimented with, and gradually stabilized in everyday work. Data was collected at the company's headquarters between early June and August 2025. The observation period was chosen, because it represents the official initial adoption period of generative AI tools for employees of the company. During this period, employees had access to the generative AI tools Microsoft Copilot and ChatGPT. Both free and paid versions were used in practice. Although formal guidelines existed, AI use was not yet fully standardized, allowing individual workers discretion in how and when they integrated the technology into their routines.

A purposive sampling strategy was applied to identify information-rich cases. Participants were recruited informally on site and selected based on three criteria. First, participants had to actively and regularly use generative AI in their daily work. Second, they had to be willing to participate in two shadowing sessions and a follow up interview. Third, sampling aimed to capture diversity across organizational roles while also identifying comparable underlying routines where possible. Seven participants were selected from sales, controlling, marketing, engineering, and management assistance. All seven participants were observed and interviewed.

The study triangulates two different data sources to increase analytical rigor and follows a longitudinal setup consisting of two rounds of in person shadowing approximately six weeks apart, complemented by semi structured interviews conducted after the second observation round. Observation round one took place in early to mid-June 2025, while observation round two occurred in late July to early August 2025. All interviews were conducted in mid-to-late August 2025. This design enabled comparison of enactment practices over time and supported the identification of stabilized, emerging, and disappearing practices. The primary unit of analysis is the individual performance within a work routine. Individual performances represent concrete instances where human actors and generative AI interact in practice. By comparing performances within and across participants and over time, inferences can be made about

how broader work routines are reconfigured. Table 3 provides an overview of participants, observed performances, and associated routines.

Table 3: Participants, Performances and Routines

Participants	Individual Performance	Routine
P04; P05	Social Media post generation	Generating Marketing Content
P02	Conduct research and write quotations for customer	Preparing Customer Quotations
P07	Analyzing sales data	Monthly Reporting
P01	Research to create concept for product testing	Product development
P06	Developing automated tool for product development	Product development
P03	Creating compliance documents	Compliance Research

3.2. Data Collection

This section details the practical execution of the research strategy employed in this study. It begins by outlining the ethical compliance measures and the operationalization of theoretical concepts into observable indicators, which formed the basis for fieldwork. Subsequently, the chapter describes the sampling strategy for participant recruitment, followed by a detailed account of the two data collection methods: longitudinal observations and semi-structured interviews. Figure 3.1 provides a visual overview of this data collection process, illustrating the timeline and sequence of research activities.

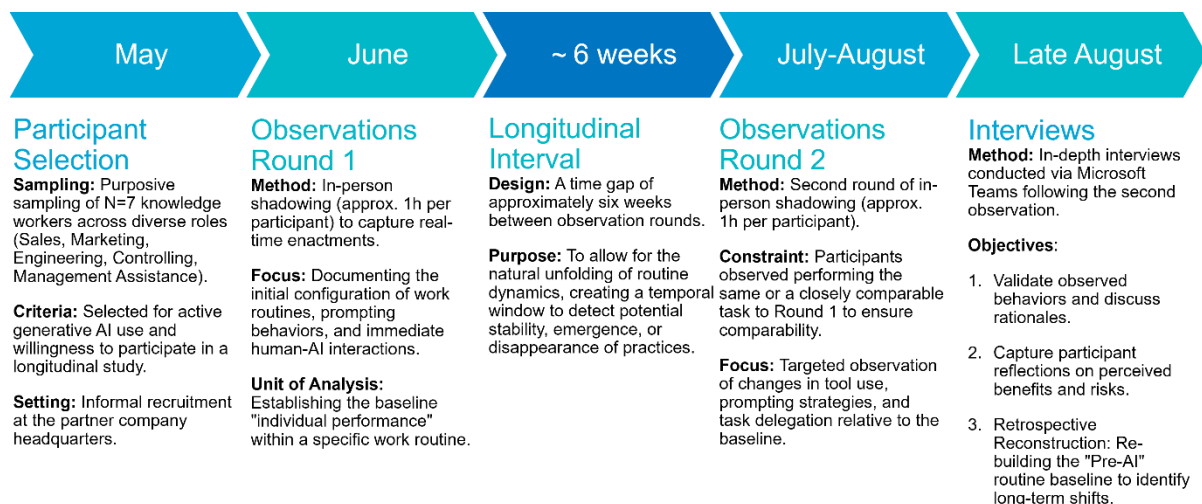


Figure 3.1: Visualization of Data Collection Timeline

3.2.1. Ethics Approval

The research design and data collection were approved by the Human Research and Ethics Committee (HREC) of TU Delft. All participants voluntarily took part in the study and signed informed consent forms, which had previously been approved by HREC. The data management plan has been revised and approved by a Data Steward of TU Delft.

3.2.2. Operationalization

To empirically investigate enactment of generative AI within work routines, theoretical concepts from the literature were translated into observable indicators. The operationalization focused on three core concepts: enactment, work routines, and sociomaterial dynamics.

3.2.2.1. *Enactment*

Enactment was operationalized using insights from the literature on generative AI capabilities and limitations. Observational focus points were derived from mitigation practices associated with common challenges such as hallucinations, bias, and data privacy risks. These focus points guided attention to how participants formulated prompts, handled outputs, validated results, and managed data sensitivity. Table 4 shows mitigation techniques that directly address prominent limitations and challenges of generative AI, as discussed in Chapter 2.4.

Table 4: *Mitigation Technique, Observational Focus Points and Dimensions*

Mitigation Technique	Observational Focus Point	Dimension
Human-in-the-loop verification Requesting and checking references to validate information. Careful human review and awareness of subjective interpretation to detect bias. Verification of originality, monitoring outputs, and adhering to copyright compliance practices.	How are AI outputs checked, accepted, modified, or rejected?	Response handling
Grounding with external knowledge (e.g. RAG). Advanced prompting techniques (e.g. Chain-of-Thought prompting).	How are prompts/questions formulated?	Prompting
Selecting specialized reasoning models or tools.	Use of specialized tools or models?	Feature use
Avoid uploading sensitive information Anonymize or clean data. Use internal or “safe” models.	Are certain measures taken to ensure data protection?	Data-privacy safeguards
Awareness of context limitations Chunk long documents Manage input length	Is attention paid to context window (e.g. new chat per topic)?	Thread management

3.2.2.2. *Work Routines*

Work routines were examined at the level of individual performances. Attention was paid to the configuration of routines, including the sequence of steps, division of labor between human and AI, tools and artifacts used, and points where generative AI was integrated.

3.2.2.3. *Sociomateriality*

To trace sociomaterial dynamics and derive how they affect enactment and routine change, factors that affect enactment practices and can cause change are traced. These include agency shifts, meaning who/what moves action forward at different points, as well as affordances and constraints of the technology, meaning which features of the tool are taken up or resisted and which constraining factors during enactment can be observed.

Finally, to assess how enactment practices and routines change over time, temporal aspects such as whether practices are routinized or improvised as well as which practices emerge or disappear are traced. The results of the operationalization can be viewed in Appendix A.

3.2.3. *Participants*

An informal agreement was established with the partner company. Participants were recruited on site and selected based on active generative AI use, willingness to participate, and access to generative AI systems at work. The systems available to participants during the observations were Microsoft Copilot and ChatGPT. Sampling aimed for diversity across roles and departments while also identifying comparable routines where possible. Seven employees participated, representing sales, controlling, marketing, engineering, and management assistance. After verbal agreement, two shadowing sessions were scheduled. Each participant signed informed consent beforehand. Follow-up interviews were subsequently conducted via Microsoft Teams.

3.2.4. Observations

Two rounds of shadowing were conducted, approximately six weeks apart, during the summer of 2025. In each round, participants were observed for approximately one hour while engaging in their work practices. Across all participants, this yielded a total of 14 hours of observation. The purpose of the shadowing was to capture how generative AI was enacted in practice and to derive insights into the configuration of work routines.

The observation guide structured the fieldwork around dimensions derived from the core theoretical concepts: enactment, routines, and sociomaterial dynamics. This was complemented by the documentation of framework conditions, such as the AI interface and the observed activity as well as temporal markers to track stability or evolution across the two rounds. Within each dimension, cues sensitized the researcher to relevant behaviors, such as how prompts were formulated, how outputs were handled, how tasks were divided, and how agency was distributed between human and AI.

Fieldnotes were taken throughout each observation session. These consisted of descriptive notes documenting what participants did, said, and used, as well as interpretive memos. This dual focus on description and interpretation ensured that data captured both detailed activities and their potential analytical relevance. To ensure comparability and enable longitudinal analysis, each participant was observed performing the same or a closely comparable task during both rounds. The observation guide template is included in Appendix A and an example for a documented field note can be viewed in Appendix F.

3.2.5. Semi-Structured Interviews

Following the second round of observations, semi-structured interviews were conducted with all seven participants. The purpose of these interviews was to reconstruct the routine prior to the introduction of generative AI, to trace perceived changes in routines over time, and to complement the observational data by capturing participants' interpretations of their own behaviors. In this way, the interviews enriched the dataset by providing access to practices and meanings that were not directly observable.

The interviews followed a semi-structured format that allowed for flexibility while ensuring comparability across participants. The interview guide was structured into five parts. The opening section clarified the aim of the study, the handling of data, and the participant's organizational role and task portfolio. The second part focused on the current routine in which generative AI was integrated, both in general terms and in relation to the individual performance observed during the shadowing sessions. Here, participants were asked whether AI was consistently used for particular steps, which parts of the task were deliberately kept manual, and how they decided when to rely on AI.

The third part addressed specific behaviors recorded in the observation notes. For each participant, two to three practices were selected because they either appeared consistently across rounds or represented a change, such as the introduction of a new practice or the discontinuation of an earlier one. These behaviors were discussed to validate the observations and to understand the reasoning behind them.

The fourth part focused on reconstructing the pre-AI routine. Participants described how they had previously approached the same type of routine, including the sequence of steps, the tools and documents relied upon, and areas of particular effort or difficulty. Establishing this baseline enabled identification of continuities and discontinuities once AI was introduced.

The final part invited participants to reflect on how their routines had changed overall. They were asked to describe the benefits and challenges they associated with AI use, as well as their expectations regarding whether their practices would stabilize or continue to evolve. All interviews were audio-recorded and transcribed verbatim with prior informed consent. Interview durations varied between 20

and 45 minutes per participant. The full interview guide is included in Appendix B and an example for an interview transcript can be found in Appendix G.

The semi-structured interviews were conducted remotely using Microsoft Teams. They followed established best practices for qualitative interviewing to ensure depth, openness and comparability across participants. Each interview began with a short warm-up to build rapport and create a comfortable setting, which is essential for encouraging the participants. Questions were structured in a funnel-like sequence, moving from broad descriptions of the participant's role and routine to more specific aspects of how generative AI was used. Throughout the interview, the researcher actively facilitated rich insights by using probing techniques such as asking for concrete examples, clarifying ambiguous statements and inviting participants to elaborate on unexpected remarks. When participants mentioned routine steps or decisions only briefly, follow-up questions (“*Can you walk me through what happened next?*” or “*What made you decide to do it that way?*”) helped uncover tacit reasoning and details that are often difficult to observe directly. The interview remained flexible to allow participants to guide the conversation toward aspects they found meaningful, while still covering the core topics outlined in the interview guide. This approach balanced consistency with openness and ensured that participants' own interpretations, experiences and sensemaking processes could be captured in sufficient depth.

3.3. Data Analysis

This section describes how the collected data was analyzed to examine how generative AI is enacted within work routines and how these enactments evolve over time. The analysis followed a multi-phase thematic approach that combined deductive coding informed by the theoretical framework with inductive coding to capture practices and meanings emerging from the data.

3.3.1. Data Preparation

The final dataset consisted of 21 documents, including seven interview transcripts and fourteen observation field notes. All documents were imported into an Atlas.ti project. Familiarization began with transcript cleaning and continued with repeated, systematic reading of all documents end-to-end before the coding started. Transcript cleaning involved listening to the interview recordings in full and correcting transcription errors to ensure accuracy, coherence, and readability. This step was undertaken to establish a reliable basis for subsequent analysis and to prevent analytic decisions from being influenced by the transcripts.

After transcript verification the interview transcripts and observation field notes were read in full to gain an initial sense of the data. This phase supported early analytic orientation and sensitivity to recurring practices, variations across participants, and preliminary indications of change over time. Notes taken during this familiarization documented emerging patterns, points of analytical interest, and instances that appeared to align with or challenge the concepts derived from the theoretical framework.

3.3.2. Analytical Phases

Phase 1: Initial Coding Setup

Before coding began, a preliminary code list was developed based on the observation guide and the operationalization of the key theoretical concepts guiding the study, namely enactment, work routines, and sociomaterial dynamics. These initial codes provided a deductive analytical structure and were closely aligned with concepts such as routine steps, prompting practices, affordances, constraints, and agency. In addition, temporal markers such as pre-AI and post-AI were already set up in the atlas.ti

project. The aim of this initial setup was not to impose a fixed structure on the data but to establish a theoretically informed starting point for systematic analysis.

The preliminary codes and associated code groups were configured in Atlas.ti prior to coding. This setup established a consistent starting point across documents while allowing the coding framework to remain open to refinement as analysis progressed.

Phase 2: Coding

All documents were uploaded into Atlas.ti and organized in two ways: by document type, distinguishing interview transcripts and field notes, and by participant, grouping all materials belonging to the same individual. The first coding cycle proceeded by coding all observation field notes, followed by all interview transcripts. This sequencing ensured that practices observed during the observations informed the interpretation of participants' retrospective accounts and reflections.

During this phase, the predefined deductive codes were applied across the dataset. Coding remained flexible, and when data segments did not fit the existing coding framework, new inductive codes were created. Examples of inductively developed codes included participants *perceived benefits* of generative AI, *perceived risks* associated with its use, and *outlooks* regarding future integration of AI into their work routines. These inductive codes captured aspects of meaning making and expectation that were not fully anticipated during the initial operationalization and thus emerged inductively.

During coding cycles, reflexive memos were used to document coding decisions and document early theme concepts and findings. Following the initial coding cycle, further coding rounds focused on participant level subsets. For each participant, both observation field notes and the interview transcript were coded together to support within case comparison across data sources and time points. This approach enabled a more holistic understanding of each participant's enactment practices and facilitated the identification of consistencies and discrepancies between observed behavior and narrated accounts.

During subsequent coding cycles, the coding framework was iteratively refined to better reflect the empirical material. Several codes were merged when they captured overlapping or closely related practices. For example, early affordance codes such as *affordance: document upload*, *affordance: document generation*, and *affordance: data visualization* were consolidated into the broader code *affordance: automation*, as these practices consistently reflected the automation of artifact production within routines rather than distinct analytical phenomena.

Conversely, some codes were split into more fine-grained ones to enhance analytical precision. A broad code capturing *human agency* was divided into more specific enactment codes such as *human steers AI* and *final edit by human*, as shifts in agency proved difficult to identify reliably at a higher level of abstraction. This refinement allowed for more precise tracing of how responsibility and control were distributed between human actors and generative AI in concrete routine performances.

Codes that occurred only sporadically or did not contribute distinct analytical value were removed during this refinement process. As such, for example, codes for specific features were omitted e.g. *Feature: Reasoning Model* or *Feature: Agent Mode*. Throughout these iterations, a structured codebook was maintained and updated to document code definitions, inclusion criteria, and changes over time. This supported consistency in code application and transparency in analytic decision making.

Phase 3: Comparative and Longitudinal Analysis

To capture temporal dynamics, marker codes such as *pre-AI*, *post-AI*, *stabilization*, *emergence*, and *disappearance* were defined deductively prior to coding. A practice was coded as stabilized when it was observed in both observation rounds. Practices were coded as emerging or disappearing when they appeared or vanished between the first and second observation rounds. These markers enabled systematic identification of change and continuity over time. The codes *pre-AI*, *post-AI* were used to

mark participant's reflections on routines, for example when they were described in the interviews to clearly separate which descriptions refer to pre-AI routines and which to post-AI routines.

Within case longitudinal analysis compared enactment practices across observation rounds for each participant and related these observations to interview accounts, including reconstructions of pre-AI routines. This comparison made it possible to identify how individual performances changed over time and how participants reflected on these changes retrospectively.

Cross-case comparison was then used to identify patterns shared across participants and routines, as well as variations. Atlas.ti features such as code co-occurrence tables, code document tables, document group filters, and matrix-based comparisons were used to support these analyses and to explore relationships between codes across documents and time points. For instance, routine steps were analyzed per participant and across cases using the document group filters *pre-AI* and *post-AI* to depict changes in routine configurations. These analytical tools supported systematic comparison while maintaining close connection to the underlying data.

Phase 4: Theme Construction

Themes were developed after coding was largely complete. Codes were elevated to themes when they occurred across multiple participants, formed a coherent and analytically meaningful pattern within the dataset, aligned with the theoretical lens, and contributed to explaining how generative AI is enacted within work routines and how these enactments evolve over time. Theme development was supported by within case summaries that captured participants' enactment trajectories and specific details. Further, cross case comparison was used to assess the recurrence and variation of patterns, and longitudinal analysis to examine how practices changed or show signs of early stabilization over time. Through this process, themes were refined to capture both shared enactment patterns and the dynamics through which routines were reconfigured over time.

4. Findings

This chapter presents the empirical results of the study, drawing on the two data sources observations and semi-structured interviews. The research followed seven knowledge workers over several weeks to understand how generative AI is integrated into their professional routines and how these practices evolve through repeated enactment. The findings are organized to provide both a detailed account of observed behaviors and a deeper understanding of the participants' internal rationales and reflections. The chapter is structured into four main sections. First, the findings from observations are presented. This section details the performance of the routines. It focuses on the technical and behavioral shifts between the first and second rounds of data collection, specifically looking at tool choice, prompting structures, and how the division of labor between human and machine manifested in real-time work. Next, the findings from the interviews are presented. This section reconstructs the transition from pre-AI workflows to human-AI collaborations and explores the participants' reflections on expertise, delegation, and perceived risks. Then, the observational and interview data are synthesized into four overarching themes. These themes explore the integrated findings from both data sources and reveal insights into how generative AI is enacted in practice and how this enactment evolves over time. Finally, the primary results are distilled, providing a transition to the discussion of how these findings relate to existing theory and work practice. By combining direct observation of AI use with the subjective experiences of the users, this chapter aims to move beyond a snapshot of adoption to reveal the nuanced process of how human intent and material agency are woven into new, stabilized patterns of work.

4.1. Findings from Observations

This section presents the findings from the observational data across two rounds of data collection for the seven participants of this study. The synthesized findings per observation round as well as the changes between rounds are displayed in table 5. The table has been synthesized from individual evolution matrices for each participant, which display findings per observation round as well as noticed changes between rounds and can be viewed under Appendix E. The analysis focuses on how generative AI is embedded into everyday work practices, how these practices evolve over time, and which conditions shape their enactment. The findings are structured along four analytical dimensions: framework conditions, routine structure and division of labor, enactment practices (prompting, response handling, privacy/thread management) and sociomaterial dynamics (agency shifts and the role of affordances and constraints).

Table 5: Synthesized Findings from Evolution Matrices

Category	Round 1 Observations	Round 2 Observations	Change Between Rounds
Observed Activity	AI was used for a wide range of knowledge-work tasks, including research, writing, analysis, programming, marketing-content generation, and administrative or compliance-related activities.	The same general types of tasks continued to be supported by AI, with two shifts towards related activities within the same work routines.	AI integration remained largely stable with two adjustments in the specific tasks supported.
AI Interface	Participants mainly relied on chat-based AI tools, sometimes using more than one system in parallel or combining chat interfaces with Microsoft Office software integrations.	Chat-based tools continued to dominate, but use increasingly concentrated on a single system, most often ChatGPT. Alternative tools or integrations were used less frequently.	Shift towards a single chat-based interface, with the parallel use of multiple systems or systems integrated into Microsoft Office being abandoned.
Routine Structure & Division of Labor	AI was typically integrated early in the workflow (with one exception where integration occurred mid-process). AI contributions primarily involved research and drafting	The basic division of labor stayed the same, with early AI integration and human validation. In several cases, additional subtasks were delegated to AI (e.g. ideation,	AI support expanded slightly, but human oversight and final responsibility remained unchanged and central. Increased experimentation with

	(text/code), while humans consistently performed validation/verification and often handled final document generation, formatting, and quality control. Collaborative text refinement was common.	document generation attempts or image generation), while participants continued to retain responsibility for verification and finalization. In some cases, tasks were explicitly reclaimed by the human when AI outputs did not meet requirements (e.g., document generation or analytical steps).	delegating additional steps to AI was often reversed when constraints were experienced.
Enactment Practices	Prompting practices ranged from brief to highly context-rich and were commonly iterative, with trial-and-error used when outputs failed expectations; while advanced techniques (e.g., role framing, custom GPTs, or cross-model comparisons) appeared in some contexts, they were not widespread. AI outputs were typically carefully reviewed, manually edited, and verified against trusted sources, and data privacy safeguards were consistently observed through avoidance or anonymization of sensitive information or use of internal models where required. Threads were usually organized task- or topic-based.	Prompting became more structured and goal-oriented, with greater use of role framing, audience or tone markers, and retrieval-augmented approaches, alongside stabilized use of pre-made prompts and custom GPTs. Iterative refinement persisted but was sometimes reduced, while variant exploration remained limited and cross-model comparison largely disappeared. Review and verification stayed standard, with manual edits increasingly focused on targeted or stylistic changes, and privacy practices and topic- or task-bounded interactions remained largely stable, aside from minor inconsistencies.	Overall, prompting became more systematic and deliberate, with reduced trial-and-error and more stable formulations. Human checking and correction remained essential, with only minor reductions in editing effort, while data privacy safeguards and thread management largely converged toward stabilized practices, with occasional minor exceptions.
Sociomaterial Dynamics	AI was primarily used for text or code generation and refinement, with users variably following system-suggested next steps and sometimes realizing affordances such as specialized configurations or multiple model variants. Constraints included output quality issues, context loss, formatting misalignment, and performance problems, though some cases reported no constraints.	Affordance use diversified to include agentic web retrieval, model switching, image generation, and attempted document generation, with suggested next steps either consistently followed or avoided. Constraints persisted, especially in advanced features. Which often led to iterative refinement or manual edits, while some cases continued to experience none.	AI use expanded beyond basic drafting, but participants selectively adopted features they deemed reliable. Ongoing reliability, formatting, and performance constraints shaped enactments through adjustments and manual overrides and, in some cases, led to narrowing tool or model choices.

4.1.1. Framework Conditions

In the observed instances, AI systems were used for a wide range of knowledge-work tasks, including research, writing, analysis, programming, marketing-content generation, and administrative or compliance-related activities. In most cases, the focal activity observed in Round 2 (which took place approximately six weeks after the first round) closely resembled Round 1, with minor alterations for most participants due to the circumstances of a live work environment. In two cases (participants 1 and 6), the observed activities were different between rounds but can still be attributed to the broader context of the same underlying work routine.

In general, participants primarily relied on a chat-based AI interface, with some participants preferring ChatGPT and some Microsoft Copilot. In the first observation round, some participants employed both ChatGPT and Copilot simultaneously and compared the results and one participant used the Microsoft Excel integration of Copilot next to the chat interface. Between rounds, a shift was noted towards a single chat-based interface, predominantly ChatGPT, while parallel use of multiple tools and the use of the Microsoft Office-integrated system were dropped. This indicates that after an initial experimentation period with multiple systems, a preferred solution became dominant for each participant.

4.1.2. Routine Structure and Division of Labor

AI was typically integrated early in the workflow, with one exception for participant 7, where the integration occurred in the middle of the activity after the participant manually executed the first steps. AI contributions primarily involved research and generating text or code, while humans consistently took over for the final steps of validation and verification of the AI generated output or handled the final document generation and formatting. The refinement of the generated text was often done collaboratively, where the participants both adjusted texts themselves and prompted the AI system to refine the text further. Between rounds, this basic division of labor stayed consistent. In some cases, the AI integration expanded slightly and additional subtasks, such as image generation for participant 5 or attempts for document generation for participant 3 were added and delegated to the AI. However, in some cases, tasks were also reclaimed by the human when the AI output did not meet requirements, for example data analysis for participant 7. Human oversight and responsibility for verification and finalization remained consistent across rounds and participants.

4.1.3. Enactment Practices

At the level of enactment practices, several changes between rounds were observed. Prompting practices in Round 1 varied widely, ranging from short, minimal instructions to detailed, context-rich prompts. Iterative prompting was common, with participants refining outputs through follow-up requests. In some contexts, prompting involved trial-and-error or comparison across different models.

By Round 2, prompting practices tended to become more structured and standardized. Participants more frequently employed role framing, explicit target or audience specifications, or in one case pre-made reusable prompt templates (participant 2). While iterative refinement remained part of interactions, it was less ad hoc in some cases, reflecting increased familiarity with how to formulate prompts to receive the desired outputs. Cross-model comparison of different variants, which was present in Round 1 in a minority of cases, largely disappeared in Round 2.

Response handling practices showed a high degree of continuity. Across both rounds, AI outputs were rarely accepted without review. Participants consistently engaged in checking factual accuracy, validating numerical information where relevant, and editing content before reuse. However, in Round 2, manual editing sometimes became more targeted, focusing on stylistic or localized adjustments rather than extensive rewriting, as was the case with participant 5.

Across both rounds, most participants consistently avoided entering sensitive or confidential information into AI systems or employed anonymization strategies when working with internal data. These practices were not experimental but appeared routinized, indicating that privacy constraints were already internalized and continued to shape how AI could be used. Participants generally organized interactions by task or topic, although minor inconsistencies persisted, where the same thread was used for different tasks or topics.

4.1.4. Sociomaterial Dynamics

Additional observational points of interest relate to sociomaterial dynamics, specifically the role of affordances and constraints, as well as the shifting distribution of agency between the human user and the technology. The observational data reveals a dynamic sociomaterial interplay, where the distribution of agency is continuously negotiated through the realization of technological affordances and the limitations imposed by material constraints. This interplay between human and material agency was visible in how features were employed, how constraints of the system blocked certain actions and in who or what steered the enactment at any given moment.

The distribution of agency became particularly apparent in "who or what steered" the performance. For instance, steering was visible when models provided suggestions for next steps. In instances where participants followed these suggestions, the system exerted a form of material agency by directing the subsequent flow of the routine. The technology here acts not merely as a tool but as an active participant that suggests trajectories. It was observed that in several cases, participants who followed suggested next steps in Round 1 also did so in Round 2, for instance participant 3.

In Round 2, the expansion of affordance use directly influenced the scope of individual performance. The adoption of "agentic web retrieval" and "model switching" allowed participants to delegate more complex, multi-step tasks to the system. For instance, by utilizing an agentic mode to collect customer data for participant 2, the routine shifted from a series of manual search-and-copy actions to a higher-level management task, where the human's primary role became the orchestration of the AI's autonomous search. Similarly, the introduction of "image generation" for participant 5 enabled the emergence of a new step, which was previously absent or outsourced. These affordances thus expanded the scope of the enactment, by making new actions feasible.

Conversely, persistent material constraints narrowed tool choice and restricted the delegation of tasks. Constraints such as "hallucinations," "context loss," and "formatting misalignment" created friction in the workflow, often leading to a reversal of delegation. For example, when "attempted document generation" failed to meet the required structure or quality standards, participant 6 was forced to reclaim the task, manually overriding the AI's output to ensure reliability. This material agency, which manifested through the technology's inability to perform specific functions, blocked the intended automation and forced the routine to remain anchored in manual performance. In some cases, these constraints led to a "narrowing" of the tool ecology. Participants observed with certain features, often experienced reliability issues and then returned to the previous approach. Thus, while affordances offered the potential for expansion, system constraints often acted as a corrective force, pulling agency back to the human.

4.1.5. Summary of Main Findings from Observations

In summary, the observational findings indicate that generative AI was a stable part of participants' everyday knowledge work, supporting tasks such as research, writing, analysis, programming, and administrative work. Over time, Interface choices narrowed from parallel experimentation to reliance on one primary chat-based system, most often ChatGPT.

Work routines showed a consistent division of labor. AI was typically used early for ideation, research, and drafting, while participants retained responsibility for verification, quality control, formatting, and final outputs. Some additional subtasks were trialed in Round 2, which in some cases proved successful, but in other cases were rolled back when results did not meet requirements.

Enactment practices shifted mainly in how people interacted with the AI system. Prompting became more structured and targeted, while cross-model comparison largely disappeared. The use of pre-made prompts as stable artefacts appeared in the second round. Output handling remained cautious, with stabilized thorough checking and selective edits.

Enacted affordances slightly expanded in round 2 for some participants while remaining stable for others. Constraints such as hallucinations, formatting limits, context loss, and latency continued to shape work by requiring manual checks and occasional overrides.

4.2. Findings from Interviews

This section presents the findings from the semi-structured interviews, which were conducted with the seven participants of this study shortly after the second round of observations. The interview data complements the observational findings by reconstructing how participants describe their work routines before the use of generative AI, how these routines were perceived to change through AI integration, and which rationales and boundaries shape the delegation of tasks to AI systems. In addition, participants reflect on perceived benefits and risks as well as on their learning experiences and expected future developments. All quotations from participants are translated from German. Original wording was retained as closely as possible while ensuring readability in English.

4.2.1. Work Routines Before and After AI

Across interviews, participants described pre-AI work routines as strongly shaped by tedious manual work, particularly manual information search and synthesis using traditional web search. Participant 1 described the workflow for research before access to AI:

“99.9% Google. [...] start with a broadly defined keyword [...], scan the page 1 hits, open 7 to 9 tabs and then go through them [...]. In short: start broad, channel it, work your way in.” (P01, Interview, ¶149-150).

The quote illustrates a time-consuming research process based on traditional web search, which is described in similar manners also by other participants, for example participant 3.

In several accounts, pre-AI routines are described as distributed across multiple actors, requiring coordination, either with colleagues or external experts. For instance, in sales participant 2 described customer data research as a task partly delegated to support roles:

“Then we had to identify contact persons, with email addresses or previously even postal addresses. Some data were already in the system, some were researched on the internet by temporary staff or trainees.” (P02, Interview, ¶95)

In marketing, participant 4 described how content production relied on interpreting and reworking existing materials from colleagues:

“There was a blog post beforehand. I looked at it (what did the colleague write?), pulled out lines/aspects and roughly summarized them.” (P04, Interview, ¶171)

Both quotes indicate that coordination with team members was a necessary part of the routine. After AI integration, participants noted a shift toward consolidated single-person workflows. Participant 2 described how researching customer data which previously involved multiple actors has changed to a single-person workflow:

“[...] trainees and temporary workers no longer have to spend time on the rather tedious task of researching addresses. Now, one person can complete the preparation in a short amount of time.” (P02, Interview, ¶113).

So, the support of trainees and temporary workers is no longer needed for the research. Similarly, after AI integration, the way research is conducted has changed. Participant 3 described this as follows:

“With Copilot, research is firstly faster and secondly I can have it pre-structured [...]. Previously I collected content and structured it myself; now the AI can pre-structure it.” (P03, Interview, ¶31).

This indicates a shift from collecting and structuring information manually to delegating pre-structuring to AI. Participants frequently mention how AI is integrated for specific tasks within the routine, such as researching and drafting, while the human role shifts towards validating and checking the generated output. Participant 6 explained this role change explicitly:

“Now the main work is rather to check whether what the AI does fits [...].” (P06, Interview, ¶120)

According to this participant the main focus of the human is now assessing the AI generated output. In some cases, participants also describe that AI integration changed the scope of what was considered part of the routine by making additional steps feasible. For participant 7, the introduction of explanatory writing was described as a new component enabled by AI support:

“What has changed most is the explanatory note: that did not exist from my side before. Now the AI provides, with relatively little effort, once the prompt is in place, a good, short overview of the evaluated data and charts. This way, recipients of the files get the most important results in two, three, four sentences.” (P07, Interview, ¶152)

An extra step was added to the routine, which was previously too time-consuming when done manually, but is now feasible, enabled by the technology.

It becomes apparent that AI does not automate the entire work, but instead individual tasks are selectively delegated to the AI system. When reflecting on why certain tasks are delegated to AI, while others are kept executed manually, participants reveal various reasons behind these delegation decisions.

One reason concerns the perceived complexity of the underlying task. For less complex steps, AI is often perceived as not necessary because the value AI integration would bring is perceived as too low:

“If I am simply looking for a screw, I do not ask AI [...]. Then Google is enough, I open the first hits and have an ‘unambiguous hit’.” (P01, Interview, ¶32).

“The individual process steps are relatively simple: click here, update a formula there, and so on. That is why I mostly did not use AI.” (P07, Interview, ¶30).

Both participants expressed that for low complexity or straightforward tasks, AI is not used and instead, the execution is done manually, for research relying on traditional web search.

Another reason for not delegating tasks to AI relates to reliability issues, which participants describe in several aspects. First, for tasks that require high precision and exact wording, participants prefer original sources over AI generated answers because the outputs are perceived as unreliable:

“With standards I need the exact wording [...]. For 100% certainty I go directly to the original source [...].” (P01, Interview, ¶70).

This indicates that when outcomes must be exact, AI outputs are treated as insufficiently dependable compared to primary sources. Second, participants connect reliability to accountability and therefore retain final authority and responsibility over the output, which leads them to reclaim final steps:

“I always do the finalizing myself. Even if I run a text through two AI variants, it still gets my personal touch at the end. I don't always agree with the AI, sometimes I know that something else would be better.” (P05, Interview, ¶41)

This shows that even when AI is used extensively, the participants position themselves as the final gatekeepers to take over for the last steps.

Third, reliability issues are also linked to recurring functional constraints, especially when tasks require specific formatting or structured document processing. These constraints lead participants to keep these steps manual:

“Processing in Excel and Word is not good yet [...]. I currently do that manually.” (P01, Interview, ¶158).

This illustrates that when the technology produces unstable or unusable outputs in required formats, participants revert to other methods to ensure reliable results. Overall, reliability concerns shape delegation boundaries through demands for precision, retained accountability, and constraints in specific functionalities.

It can be seen how routines shifted from tedious manual work that required coordination among multiple actors to consolidated human-AI workflows in which the AI system automates certain tasks, while humans focus on validating the generated answers. The decisions which tasks are delegated to the AI, depend on complexity, stage within the routine and reliability concerns often based on previous experiences.

4.2.2. Perceived Benefits and Risks of AI Integration

During the interviews, participants reflected on the perceived changes that came with adopting this new technology. Perceived benefits were often articulated through time savings and efficiency gains. Participant 1 described research as *“significantly faster”* and emphasized that this *“saves a lot of time,”* (P01, Interview, ¶168) while participant 2 similarly noted shorter processing time and an improved end result: *“The processing time is much shorter and the quality of the end result is better.”* (P02, Interview, ¶119).

In addition, participants reported higher output quality and greater variation in generated texts. Participant 4 highlighted more variety and improved tone control, concluding that the output is *“overall better than when I write alone.”* (P04, Interview, ¶194-207).

Beyond performance improvements, some participants described a perceived increase in expertise through access to synthesized knowledge. Participant 1 noted that AI provides an entry point that makes them *“somewhat of an expert,”* (P01, Interview, ¶169) while participant 6 described that, for complex issues, AI enables more targeted interaction with experts:

“When it comes to more complex issues, you can talk to the experts in a more targeted manner because you no longer have to start from scratch.” (P06, Interview, ¶126)

This signals that both participants experienced a sense of empowerment through access to AI, enabling them to increase access to knowledge and expertise.

Alongside these benefits, participants repeatedly stressed risks related to reliability and the danger of uncritical acceptance of AI-generated outputs. Participant 1 warned that the main risk lies in convenience and the temptation to accept AI outputs without sufficient scrutiny:

“A risk is convenience: ‘swallowing’ results without checking them. For example, with standards: the AI might deliver outdated or secondary sources. Previously, with Google I could immediately see whether a hit was trustworthy. The AI just lists it, and you accept it.” (P01, Interview, ¶175)

This concern is closely tied to the perceived opacity of AI-provided references and the risk of blindly trusting synthesized answers. Beyond the immediate issue of reliability, participants also highlighted risks around professional competence and responsibility. Participant 3 expressed worry that relying on AI could erode independent problem-solving and reflective thinking over time:

“I have a subtle feeling that I might lose competence, the ability to work things out independently and think through the process completely. You become lazy.” (P03, Interview, ¶57)

Similarly, participants 1 and 6 emphasized that AI can produce outputs that appear plausible and confident while being incorrect, which may lead to an illusion of expertise when users lack sufficient domain knowledge to evaluate results. This risk was described both through observed behavior in colleagues and through broader reflections on how AI is perceived within the workplace:

“I have already seen things from colleagues that clearly came from ChatGPT but were asked in an unspecific way and left unchecked. Exaggerating a bit, AI can make people believe they are more competent than they actually are.” (P01, Interview, ¶182)

“Some colleagues think AI is a secret weapon that suddenly makes you know everything. But AI sometimes spouts nonsense. Sometimes the errors are easy to spot, sometimes more difficult. Especially if you are not an expert in the field, there is a risk of being misled.” (P06, Interview, ¶132)

Together, these accounts show that perceived risks extend beyond technical reliability to concerns about how AI reshapes judgment, accountability, and competence. The technology is therefore treated as valuable but requires continued critical evaluation and deliberate safeguards.

4.2.3. Reflections on Learning, Skills and Future Use

When reflecting on their experiences since the adoption of AI systems, participants described AI integration as associated with learning processes unfolding over time. These learning processes are often shaped by trial-and-error approaches, which eventually lead to evolving practices. One recurring element is the development of more structured prompting practices. Participant 2 described a learning curve from trying inputs spontaneously toward clearer knowledge of what information needs to be included, and reported saving prompts for reuse:

“At the beginning you feel your way in and try out what comes out. Gradually you learn how to enter prompts so that the answers fit. [...] At the beginning I just entered something and then added ‘please more detailed’, ‘please more professional’, ‘please include this as well’. In the end I knew what had to go into the prompt so that it fit straight away. I saved these prompts so that I do not have to write them from scratch every time, I only adapt them for the particular request now.” (P02, Interview, ¶77; ¶83)

This shows how learning from continuous enactment over time leads to more stabilized workflow patterns and practices for the participant. Learning is also explained as increased strategic awareness in how tasks are framed before interacting with AI. Participant 6 emphasized pre-structuring and goal clarification before prompting:

“By now I first think without ChatGPT: what do I actually want? Otherwise you quickly get a bit lost because ChatGPT also needs to know what I am aiming for. So first the basic structure in my head, where do I want to go, what do I want to achieve, and then I use ChatGPT.” (P06, Interview, ¶53)

This shows that over time the participant has developed a more targeted approach to integrating AI, which involves additional work upfront to structure and align the task.

In addition, learning is described as socially supported, for example through exchanging knowledge with colleagues. Participant 4 reported receiving a prompt cheat sheet from a colleague:

“A colleague is very skilled; this colleague sent me a cheat sheet with prompts. We support each other and benefit from one another.” (P04, Interview, ¶117).

This indicates that knowledge around prompting and effectively enacting AI is shared among peers.

Looking ahead, participants often anticipated continued expansion and stabilization of AI integration. For instance, participant 4 mentioned a shift toward more strategic applications beyond day-to-day

work: *“I think we will use [AI] much more, starting much earlier [...] more strategically.”* (P04, Interview, ¶297)

This signals that AI integration is likely to expand within this routine towards deployment in earlier steps and for alternative use cases, here: strategic planning.

4.2.4. Summary of Main Findings from Interviews

Across participants a shift from pre-AI routines dominated by manual information search and processing to consolidated human AI workflows in which AI supports specific steps such as research, information synthesis, and drafting was described. This shift also entails a reduction in coordination steps that previously relied on input from additional actors, for example in customer data preparation and marketing content development.

At the same time, AI integration was described as selective rather than end-to-end. Participants reported that AI is integrated where it adds value and where outputs can be checked, while humans retain responsibility for evaluation, validation, and final decisions. This includes a reported role shift toward checking whether output fits the work context and a continued emphasis on final authority over the output.

Delegation decisions were described as contingent on task characteristics and prior experiences. Low complexity steps are often kept manual, particularly when traditional search is considered sufficient. Tasks requiring high precision were also reported as more likely to remain manual due to concerns about unreliable AI generated answers. In addition, previously experienced constraints, for example around document processing and structured output formats, limit delegation and lead to continued manual execution of these steps.

Participants frequently mentioned perceived benefits, such as increased efficiency through timesaving by automating extensive manual work, higher output quality, for example, for generated texts, and heightened expertise, due to access to synthesized specialist knowledge. However, alongside these benefits, participants highlighted risks related to reliability and uncritical adoption of AI-generated answers. Further, risks in relation to professional competence and responsibility as well as data privacy were expressed in multiple cases. This shows that generative AI as a technology is neither perceived as entirely beneficial or entirely dangerous but instead as a technology with high potential for improvements, which also requires careful application and awareness of underlying risks.

Finally, participants mentioned learning processes that unfold over time. These include, for example, increasingly structured prompting practices or more strategic task framing before prompting as well as peer supported learning. Looking ahead, most participants anticipated further expansion and stabilization of AI integration, including potential movement toward earlier or more strategic stages of work.

4.3. Integrated Findings

This chapter presents the integrated findings from the observations and the interview data. The analysis of both data sources resulted in four interrelated themes, which are presented in detail below:

1. Generative AI as a flexible collaborator in knowledge work routines
2. Reconfiguring the human-AI division of labor
3. Learning to work with the machine: emerging prompting and feature routines
4. Sociomaterial tensions around trust, control and risk

Together, these themes show how generative AI becomes a technology-in-practice through situated enactment, how routines are reconfigured over time, and how human and material agency remain tightly entangled.

4.3.1. Generative AI as a flexible collaborator in knowledge work routines

This theme captures how participants positioned generative AI less as a one-off tool and more as a flexible collaborator they engage with in cooperative dialogue. Thereby enabling a co-production dynamic, where users delegate bounded cognitive tasks like research or text generation, while retaining strategic framing, effectively expanding the scope of their routines. This speaks directly to the research questions by providing insights into which use cases emerge through generative AI and how the technology becomes woven into everyday enactments.

4.3.1.1. *Delegating bounded cognitive tasks to AI*

Across cases, generative AI was used for clearly bounded but cognitively demanding subtasks such as information search, ideation, summarization, and text generation. Participants typically retained responsibility for defining the task and verifying the output.

Interview accounts emphasized that delegation was primarily directed at early steps, while assessment of completeness, correctness, and relevance remained a human responsibility. The management assistant (P03), for example, described how AI now takes over the initial research structuring in compliance work:

“[...] Previously I collected content and structured it myself; now the AI can pre-structure it.”
(P03, Interview, ¶31)

While at the same time emphasizing that this delegation is limited to early steps, with the human taking over for the final assessment:

“Afterwards I check the sources and see whether everything has been captured or whether important additional information is missing.” (P03, Interview, ¶31)

This illustrates how AI became embedded at the beginning, taking over the cognitive work of organizing information, while validation and checking for completeness remained a human responsibility, indicating a clear boundary in the division of labor.

Similarly, the technical manager (P01) drew a clear boundary between precise, fact-based lookups and open-ended exploration. For highly specified standards the participant bypassed AI altogether, but delegated broader exploration:

“If I need the content of a very specific standard [...] I do not need AI [...] without a clear target image, then I use AI.” (P01, Interview, ¶39).

This quote illustrates how for the participant, integrating AI only becomes feasible for exploration and broad research but not for specific research.

In sales, participant 2 similarly used AI to offload preparatory cognitive work:

“[...] I definitely use AI. Of course not continuously from A to Z, but for example for wording or to get new ideas.” (P02, Interview, ¶23)

Here the participant mentioned clearly bounded cognitive tasks: “wording” and “getting new ideas” which are delegated to the AI system, while also differentiating that the system is not used continuously for the whole process (“from A to Z”). This reflects how AI is integrated for specific steps to generate options and drafts that are then selectively adopted. The second observation of participant 2 shows how this is enacted in practice. The model is prompted to propose suitable customer groups, research specific customer companies, compile an Excel sheet with company data, and generate product pitch emails in one continuous workflow. Humans are primarily focused on reading and validating outputs, checking sources and making minor adjustments.

Observation records across participants support this pattern through repeated enactments in which AI is integrated for specific bounded tasks, often early, for example for research and drafting, while participants focus on review, validation, and final output preparation. For instance, observation data for participants 5 and 3 reflect this division of labor:

“Starts task by writing prompt to generate text. Then iterative refinement of output with follow-up prompts. [...] Participant thoroughly analyses output and makes manual adjustments.” (P05, Observation Round 1)

“AI integrated in the beginning for research, then used for iterative refinement of output. Final edit and document generation done manually by participant” (P03, Observation Round 1)

In both cases, AI was integrated for specific steps, such as generating text, refining the text or researching information, while other steps deliberately remained performed by the human.

4.3.1.2. Human-AI co-writing and collegial interaction

Beyond subtask delegation, several participants described their interaction with AI in relational terms, positioning it not merely as a tool but as a sparring partner, quasi-colleague, or cooperative agent. This shift from “using” to “collaborating” was visible in both how participants spoke *about* the AI and how they spoke *to* it.

Interview data reveals that participants explicitly framed the model as akin to a coworker. Participant 1 described delegation to the AI using the metaphor of an employee:

“If I, as with an employee, say: ‘Do some research, collect everything relevant on the topic ‘ [...]” (P01, Interview, ¶39)

This metaphor frames AI interaction as social rather than purely instrumental. Several participants extend this framing through anthropomorphizing, assigning gender and personality to the system to facilitate interaction. During interviews, participant 1 noted, *“Even though we established that for me, it’s a woman.”* Similarly, participant 5 explained that treating the AI as a male “buddy” makes the drafting process more fluid:

“For me, it’s a ‘he.’ I find it easier to phrase things when I communicate ‘on a buddy basis’ – he understands that. I could also just type lists, but it’s easier for me to ‘chatter away.’” (P05, Interview, ¶131)

These descriptions show how participants actively shaped the interaction style to resemble informal human dialogue, which appears to be not only a style choice but as becomes apparent in the case of participant 5, an enabler for more effective prompting.

Observation data confirms that this framing is enacted in practice. Participants frequently used greetings, polite markers, like “*please*” and “*thank you,*”, and context-checking questions in prompts, such as “*You know our target customers right?*” (P05, Observation Round 2).

This transforms the interaction from command-based input to conversational exchange. This practice signals a shared enactment of AI as a responsive partner rather than a passive tool. Within this relational frame, the actual work of writing becomes a co-production. Participant 4 talked about AI as an extension of the participant’s creative capacity:

“My idea remains the basis. AI is a complement or improvement of what the human brings” (P04, Interview, ¶219)

This shows how the enactment of generative AI resembles more collaboration rather than the mere use of a tool for certain tasks. Similarly, participant 5 described a workflow where the AI acts as an external second reader or editor:

“What I almost always do is run drafted texts through an AI for correction or ‘rounding off’, to see where I stand and what can be improved. [...]” (P05, Interview, ¶44)

Again, this signals a stable workflow integration of the AI system in a collaborative rather than purely directive manner, where the AI is not just integrated for refining the text but also consulted for suggestions on improvements. This indicates a certain level of trust in its judgment.

Observation data for both participants confirm this dynamic: AI generates initial formulations, the participant thoroughly scans the output and either uses a follow-up prompt to have the model refine the output or adjusted it manually, for example, by deleting emojis, inserting company-specific terminology or adding sentences.

“Participant visibly reads through output line by line and makes adjustments. Refines output with follow up prompt.” (P04, Observation Round 1)

“Participant thoroughly analyses output and makes manual adjustments. Copies text into Word and edits manually. Also pastes text back into ChatGPT for another rewrite.” (P05, Observation Round 1)

Across these accounts, AI was not enacted as a black-box generator but as a conversational partner. The interaction was characterized by social norms (greetings, politeness), anthropomorphic projections (gender, “*buddy*” status), and a division of labor that mimics a senior-junior colleague relationship.

4.3.1.3. Expanding what counts as part of the routine

A recurring pattern was that generative AI enabled additional routine steps that had previously not been enacted, or not consistently, because they were too effort intensive. This includes adding explanatory notes to existing analyses, adding new steps or expanding the range of preparatory work that can be completed by a single person. For participant 7, a new step of written explanation emerged in the monthly reporting routine (see P07, Interview, ¶152) in section 4.2.1.).

The technology here enables an additional step that previously did not exist, because it was too time-consuming to generate manually. Through the integration of AI, the step becomes feasible with minimal effort and thus changes the scope of the routine.

In sales, AI automated preparatory work that used to be distributed across several people, thus changing the scope of what an individual person does:

“[...] Now, one person can complete the preparation in a short amount of time.” (P02, Interview, ¶113).

This illustrates how a previously fragmented workflow involving multiple actors has been condensed into a single-person workflow. Therefore, the scope of the individual's routine step increased and the ostensive pattern of the routine changes.

The observation records support this expansion as a shift toward adding new steps and delegating them to AI in Round 2. For instance, participant 5, who used the AI to generate an image towards the end of the performance or the addition of new steps, such as the explanatory note for participant 7. This shows how new steps become possible, enabled by the technology, which add further value to the work of the participants.

Participant 4 had not yet expanded the routine but anticipated further expansion from operational content creation to strategic planning in the future (see P04, Interview, ¶297 in section 4.2.3.). This suggests that current operational uses are paving the way for more complex, strategic integration of AI in the future, adding new steps to the beginning of the routine.

Across cases, these accounts show that AI does not affect existing steps but also makes new actions feasible within the same routine, expanding participants' understanding of what it entails. In sociomaterial terms, AI's affordances for automation and content generation enable "routine stretching": new actions become thinkable and feasible, leading to an expanded ostensive understanding of what it means to "do reporting" or "prepare a campaign".

4.3.2. Reconfiguring the human-AI division of labor

The second theme addresses how the division of labor between the user and the AI system is structured in practice and how enactments of generative AI reconfigure who (or what) takes over which steps. It further captures how these configurations remain dynamic in practice and how reconfigurations of workflows lead to consolidation of previously distributed social coordination.

4.3.2.1. *Frontloading ideation and research to AI*

Across cases, early steps such as ideation, customer selection, and information gathering were frequently delegated to AI, which shortened human preparation work and shifted human effort toward later stage checking and coordination.

In the observations, AI was typically integrated at the beginning of the workflow for most participants, with one observed exception for participant 7, where integration occurred mid process. This suggests a pattern of frontloading early-stage production work to AI while retaining human responsibility for evaluation and completion. Observational data for participants 1 and 3 highlight this pattern, although this has been observed for most participants:

"AI integrated in the beginning for research." (P03, Observation Round 1)

"AI integrated in the beginning and middle - final step of putting all the retrieved information together done by human" (P01, Observation Round 1)

These field notes show how, the AI system was integrated directly in the beginning of the observation in these cases to conduct initial research or generate drafts.

Interview accounts support this pattern. Participants frequently described how AI is typically used for early steps, such as ideation, research, generating drafts or pre structuring information.

"[...] we currently get a lot of ideas for sales emails from AI" (P02, Interview, ¶23)

"AI is great for the 'first shot' [...] I start broadly and have everything listed for me, so that I can then go into more detail." (P01, Interview, ¶51)

This shows how manual steps are replaced by automation in the early stages of the workflow and pave the way for further refinement and adjustments which are then often done collaboratively or manually by the human.

The co-occurrence table (see Appendix D) further highlights this reconfiguration: *Division of Labor: AI* regularly co-occurs with *Routine Step: Information Search / Research* and with *Routine Step: Text Draft Generation*. This pattern suggests a systematic frontloading of supporting tasks to AI and a concentration of human work in checking, coordinating, and finalizing outputs towards the end of the enactment.

4.3.2.2. *Stabilizing Human Oversight and Last Word Control*

Despite the strong delegation of early steps to AI, participants consistently retained the last word. This became apparent in interview accounts through repeated emphasis on verification, stylistic control, and responsibility for final outputs.

Participant 4 described an intensive verification layer:

“I basically always do it with AI, but I then check everything. Errors creep in, statements sometimes do not match the data source. [...] I always read through again at the end. [...] I almost always change something.” (P04, Interview, ¶51; ¶135)

This routinized checking and manual editing procedure demonstrates that trust is not blind but conditional on rigorous verification. Although the participant stated that AI is used almost all the time, which suggests a high level of trust in the system, they nevertheless mentioned an omnipresent mistrust, which leads to intensive controls and checks of the output.

During the observation, participant 4 let AI draft product-related social media content, then read the output carefully, deleted emojis, inserted company-specific wording and added a sentence manually before publication. Participant 5 similarly mentioned that the last word is consistently retained by the human:

“I always do the finalizing myself. [...] it still gets my personal touch at the end.” (P05, Interview, ¶41)

The participant described how manually editing the final version of the AI-generated text has become a stable part of the routine. This step appears to be based on a need to add a “*personal touch*” to the output as well as a general mistrust towards the technology when it comes to reliably produce high-quality content (see section 4.2.1. for full quote).

In controlling, participant 7 highlighted the importance of maintaining tight oversight over the correctness of results:

“It is important to question AI results and form your own assessment of whether the figures are plausible. [...] I check every time. I try whether the numbers are correct.” (P07, Interview, ¶90-98)

This highlights a persistent skepticism towards AI generated output, where verification is a mandatory step rather than an optional safeguard.

Observation data across participants mirrors this behavior through stable response handling practices in which outputs are reviewed thoroughly, corrected, and often manually finalized. Practices such as checking sources for research results, comparing answers to trusted sources or comparing answers from different models were frequently observed. Also, manual formatting and editing to align AI output with local requirements were common during the observations.

“Checks sources provided by the model. Does manual post-editing to condense information. Compares outputs of both models to the same prompt.” (P01, Observation Round 1)

“Participant visibly reads through output line by line and makes adjustments if necessary. Adds sentence to output manually. Adds company specific terms to output manually.” (P04, Observation Round 1)

These field note quotes reveal a commonly observed workflow structure and division of labor, where AI handles drafting and structuring, while humans perform manual formatting, company-specific adaptation and the final validation step.

Evidence from the code co-occurrence tables (see Appendix D) further emphasizes these enacted control practices. *Response Handling: thorough manual check* and *Response Handling: manual edit* have the highest occurrences of response handling practices and occur in the majority of participants, indicating that validating and editing AI generated outputs has become a new standardized practice for most participants. At the same time, these codes often co-occur with the code *Constraint: Output Quality and Reliability* indicating that thorough response handling practices are often linked to reliability issues with the AI generated outputs.

Across cases, human oversight was not only asserted but enacted in practice through thorough output assessment, crosschecking and editing steps that were consistently coded and observed.

4.3.2.3. New hybrid failure points and reclaiming work from AI

Where AI outputs prove unreliable or misaligned with requirements, hybrid routines introduce new failure points. These episodes led to additional checking work, to iterative refinement, and in some cases to reclaiming tasks from AI back to the human, particularly where features did not perform reliably.

In the observations, this was visible in persistent constraints and in repeated manual overrides, including failures around document generation, formatting alignment, system errors, and file handling limitations, which required participants to adjust workflows and complete steps manually.

For instance, participant 3, after initially having created the final document manually during the first observation, tried to automate the step with AI-assistance, only to experience failure and then handling the step manually:

“Participant merges excel sheets manually after model failed to do so” (P03, Observation Round 2)

Similarly, participant 6 experienced constraints regarding the AI-generated documents in both rounds and for each occasion had to manually correct the issues. In round 1, the AI produced runnable code and a filled document, but the result did not meet the requirements, which led to visible dissatisfaction and manual correction of the code and document structure.

“Final version did not fulfill the specified requirements” (P06, Observation Round 1)

And in round 2, the model failed to generate the document entirely:

“Participant asks model to create document but it is not created in output” (P06, Observation Round 2)

This shows the significance of human oversight and manual intervention, which is necessitated by persistent reliability issues with features of the technology.

In other cases, experiencing constraints led to ultimately reclaiming entire steps which were previously delegated to the AI-system, as can be seen, in the example of participant 7, who after having experienced significant constraints with data analysis and visualization tasks in Round 1, executed these steps

manually in round 2 and instead integrated AI for other steps. Participant 1 was observed consistently creating documents manually in both rounds, deliberately not making use of the affordance of document generation by the model.

During the interview, the participant explained this practice with having experienced persistent problems with AI-generated tables and formatting in the past:

“Processing in Excel and Word is not good yet [...] the results are often unusable. I currently do that manually.” (P01, Interview, ¶58)

This description exemplifies how constraints of the system force a fallback to manual methods when features of the technology are unreliable. These hybrid breakdowns make visible the sociomaterial nature of the routine: constraints such as output quality, memory and functional failures shape where agency resides, and when humans reassert control over previously delegated steps. The theme shows how the division of labor between humans and AI is not fixed but negotiated over time. Early enthusiasm for broad delegation can be curtailed when functional constraints become apparent, leading to hybrid arrangements where specific tasks are reclaimed by humans, while others remain stably delegated.

4.3.2.4. Consolidating social coordination into a single human-AI workflow

This theme highlights shifts in the routine’s network of actors. Where routines previously relied on distributing tasks and coordinating with colleagues or external experts, participants increasingly consolidated these steps into an interaction with the AI system. This effectively shrinks the social scope of the routine, reducing coordination needs and insulating the task within a single human-AI collaboration.

Internal consolidation: replacing delegation and coordination

In two cases, the integration of AI eliminated the need to hand off tasks to junior staff or coordinate with peers for information retrieval. In sales, the pre-AI routine was distributed across a hierarchy, where preparation work was outsourced to support staff. Participant 2 described how this coordination has disappeared after integrating AI (see P02, Interview, ¶113 in section 4.2.1.).

This created a self-contained workflow where social dependencies are removed in favor of human-machine interaction. Where prior to AI, multiple employees collaborated for a multi-step process, now a single person can perform the routine almost end-to-end.

Similarly, in marketing content creation, participant 4 illustrated how pre-AI, active engagement with previous work of a colleague was needed to create marketing content, which is now obsolete (see P04, Interview, ¶171 in section 4.2.1.). This shift eliminated the intermediate step of interpreting and potentially discussing a colleague’s work, streamlining the path from information to content but leaving out human touchpoints.

External consolidation: bypassing experts

The consolidation extended beyond the organization to external support. Participants described a pre-AI reliance on external experts, service providers, and forums to solve specific problems. Participant 6 contrasted the current immediate availability of answers with the previous need for extensive inquiry:

“Well before that we asked a lot more experts. Internally or externally. Depending on the topic: service providers, training providers, trade associations.” (P06, Interview, ¶119)

This marks a reduction in external information seeking, as AI becomes the primary interface and source for knowledge.

For participant 1, technical hurdles previously necessitated a multi-stage escalation process involving community engagement and vendor support, which eventually led to consulting an expert as a last resort. This tedious progression was described as follows:

“For very special questions [...] search forums or post myself and write to vendor support in parallel. That is the path [that leads] ‘up to an expert’ if I cannot get any further.” (P01, Interview, ¶156)

The AI short-circuits this escalation process, providing immediate answers that previously required community or expert interaction.

The observation data supports these reflections and shows how, across cases, work was enacted in practice as single user orchestrations, which is consistent with the description of consolidated human-AI workflows.

The emerging technology-in-practice replaced distributed queries and escalation ladders with a centralized dialogue with the AI model. In sociomaterial terms, the routine is decoupled from the broader social network. The human-AI partnership becomes a self-sufficient unit that absorbs tasks previously dispersed across trainees, colleagues, and external experts, thereby replacing social coordination.

4.3.3. Learning to work with the machine: emerging prompting and feature routines

The third theme analyzes how participants learn to interact effectively with generative AI, by developing micro practices around prompting, feature use and strategic framing. These practices evolved from exploratory experimentation to more stabilized scripts and support the formation of distinct *technologies-in-practice* over time.

4.3.3.1. From exploratory play to stabilized prompting scripts

Participants described a learning process in which prompting had become more structured and goal oriented, including the development of reusable prompts and the use of more sophisticated prompting techniques, such as role framing, clearer specification of target audience, tone, and output structure. These descriptions are matched by an observed evolution of practices between rounds across participants.

Observation data documents change between rounds toward more standardized prompts, as well as reusable prompt templates, and more deliberate interaction patterns that reduced trial and error in some cases while retaining iterative refinement where needed. Table 5 in chapter 4.1 highlights this development and shows how prompting practices matured across participants. In addition, the evolution matrices in Appendix E show how for each participant these practices developed individually between observation rounds. Some noteworthy examples include participant 2, who started using pre-made prompts in round 2 or participant 1, who incorporated more sophisticated prompting techniques in the second observation round:

“Pre-made prompt used. Pre-made prompt includes: role framing, Detailed output specification”
(Participant 2, Observation Round 2)

“Explains role, links website to company in prompt, Very extensive prompt” (Participant 1, Observation Round 2)

Both instances reveal a gradual shift towards more sophisticated prompting methods within the 6 weeks between the two observation rounds.

The co-occurrence table supports this by showing that overall, more sophisticated prompting practices emerge between rounds, while other practices such as extensive prompts or iterative prompting stabilize.

During reflections, participants frequently reported an initial phase of trial-and-error prompting at the beginning of adoption, followed by a learning curve regarding the formulation of prompts. Over time, participants started to develop more elaborate prompting strategies with reusable prompt templates and more strategic question design. Participant 7 described this development:

“Over time [...] I worked out how to use AI and how to ask questions so that better information comes back. There was definitely a development step, and I saw that it is possible to integrate AI into the tasks.” (P07, Interview, ¶57)

This shows how the learning process of how to formulate better prompts not only led to improved outputs but in turn also to additional applications, due to the increased usefulness. Participant 2 had undergone a similar learning experience and described how prompting practices evolved from trial-and-error to template-based use, marking an early stabilization of the practice (see P02, Interview, ¶77; ¶83 in section 4.2.3.). The participant had first developed effective prompts through learning experiences and then saved successful prompts for reoccurring tasks, making the overall routine more efficient.

For participant 4, saved prompts became part of a stabilized workflow:

“I have already prepared a prompt so that I do not have to start from scratch every time. It is not perfect yet, but I am working on it.” (P04, Interview, ¶75)

Like other participants, also here, learning experiences over time have led to the development of effective prompts. In this instance, the learning experience appeared to be still ongoing.

The reflections, together with the observational data confirm that effective use was not immediate but the result of an iterative learning process and illustrates how the interaction with the AI system moves from explorative to more routinized patterns, which led to better results for the participants and expanded the usability.

4.3.3.2. Selective feature adoption and emerging tool ecologies

Feature use also evolved over time yet remained selective. Participants experimented with different modes and features, such as image generation, agent mode or switching between models, but rarely exploited the full available functionality.

Observational data reveals that feature use increased between rounds and in several cases, participants adopted or experimented with new features in the second round. For instance, participant 2 integrated the agent mode feature in round 2 to collect customer data, used document generation functionality and switched between models for different steps. All of these practices were not observed in the first observation round.

“Changes between models. Gpt 5 for brainstorming / idea finding task. Agent mode for collecting customer data.” (Participant 2, Observation Round 2)

These practices show a rather feature-rich enactment, utilizing multiple available features in one workflow. Similarly, participant 6 employed the agent mode, let AI generate a document and switched between models in round 2. Participant 3 started experimenting with the document generation feature in the second observation round after refraining from it in the first round and instead created the document manually:

“Lets AI create document (excel sheet).” (Participant 3, Observation Round 2)

This shows how over time the integration of features expanded as participants learn how to deploy them. By contrast, other participants continuously resist certain affordances. Participant 1 manually copied AI

output into Word instead of using built-in document creation in both rounds and did not use different models or customization, although available.

Further, across participants, the observation data highlights that generative AI was embedded into existing tool ecologies. Several enactments include parallel use of classic search engines, Word, Excel, OneNote and other office tools. The resulting practice is not *using AI instead of tools* but using AI alongside and through them.

4.3.3.3. *Strategic task pre-structuring and thread management*

Participants gradually developed specific ways of interacting with the AI that allow them to apply it in a more targeted and strategic manner. This often led to better results and expanded application of the technology.

Observation data reveals that most participants showed consistent thread management and stayed within a single topic per session, although in two cases a shift towards inconsistent thread management between rounds was observed. Table 5 in chapter 4.1 summarizes the overall thread management patterns across participants and the evolution matrices in Appendix E reveal the respective practices per participant. The field note data exemplifies these practices and how they show signs of early stabilization, for example for participants 7 and 1:

“Old chats are deleted before retries in copilot excel” (Participant 7, Observation Round 1)

*“Stays within same topic in one thread
Opens new chat for different topic”* (Participant 1, Observation Round 1)

“Opens new chat when first task is started” (Participant 1, Observation Round 2)

In addition, several other more strategic practices became apparent in the observations. For instance, participant 2 kept one chat per campaign but stored standard prompts in OneNote as reusable components, indicating an emerging temporal structure where AI sessions are anchored by stable prompt artifacts.

During the interviews, several participants reflected on learning processes leading to newly acquired strategies for more targeted AI interactions. These strategies were often based on previous trial and error approaches. As such, participant 6, reflected on the learning process and described the need for clearer task definition before engaging AI:

“I first think without ChatGPT: what do I actually want? [...]. Then I use ChatGPT.” (P06, Interview, ¶53).

This cognitive pre-structuring ensures that AI is used to execute a clear intent rather than to define it. Although the pre-structuring and framing ahead of AI integration requires additional effort, the participants’ reflection indicated that the measure is ultimately required for effective AI integration. In a similar manner, participants 5 and 7 mentioned the necessity of strategic guidance when interacting with the AI.

“You have to keep asking yourself: What is the aim of the article?’ Focus on that, then it will work.” (P05, Interview, ¶181)

“For larger tasks, it makes more sense to go into the prompt with a clear direction and detailed wording.” (P07, Interview, ¶111)

Both participants independently arrive at the conclusion that precise inputs are necessary to extract value from the system, highlighting the importance of framing and structuring the task through the human before engaging with the AI.

Overall, these findings illustrate a maturation in practice where the work of using AI increasingly shifts upstream moving from reactive adjustments within the chat to proactive cognitive structuring and organized thread management before the interaction begins.

In total, Theme 3 shows how prompting, feature use and interaction sequencing evolve from improvisational experimentation toward relatively stabilized practices, consistent with routine dynamics perspectives on how repeated performances generate new ostensive patterns.

4.3.4. Sociomaterial tensions around trust, control and risk

The fourth theme synthesizes how participants negotiate trust in AI outputs, data privacy, professional identity and perceived capability loss. These tensions shape when and how AI is enacted and highlight the inseparability of social and material aspects of the routines.

4.3.4.1. *Negotiating trust in AI outputs*

Participants expressed both appreciation for AI's efficiency and deep concern about the reliability of its results. The central tension here is not about the user's skill, but the tool's veracity. Participant 1 warned against uncritical acceptance, particularly in technical domains and identified a specific risk where the ease the AI system brings threatens critical evaluation (see P01, Interview, ¶175 in section 4.2.2.).

This illustrates a tension whereby an affordance of the system (condensed and structured presentation of information) is also perceived as a risk because of lacking transparency for sources. The participant seems aware of this and appears to balance the increased efficiency through the AI, with the necessity of safety measures to validate information.

In Marketing, participant 5 described how trust is constantly negotiated during enactment, depending on the quality of the output:

“Sometimes there are texts where I think: ‘I could not have done it more beautifully’, then I do not have to do anything. Sometimes I think: ‘Wrong movie, absolutely not.’ Then I finish it myself or mix two suggestions. [...]” (P05, Interview, ¶101)

This oscillation reflects a more ambivalent trust stance, due to the unpredictability of the AI output. Some outputs are indistinguishable from what the participant would have written, others are rejected entirely. Thus, requiring the participant to constantly assess whether to accept or override the output. This selective acceptance demonstrates that trust is evaluated on a case-by-case basis depending on output quality. Each output is assessed and depending on the human judgement, the result is either accepted or manually adjusted. As there are often no hard criteria for “beautiful” marketing content, this requires strong judgement skills and signals a shift in the role of participant 5 from content generator to content validator.

Observation data show how these ambivalent trust positions are enacted in practice. As mentioned before and indicated in table 5 of chapter 4.1, thorough validation and manual checking procedures were observed across participants and rounds. Further, during observations, participants often showed ambivalent stances towards trust in the AI system. For instance, participant 3 repeatedly followed AI suggested next steps, while at the same time refrained from document generation functionality and displayed extensive manual final editing:

“Participant follows suggestions of AI but also appears to be rather critical of results. Copies output into word document manually - doesn't let AI create document” (Participant 1, Observation Round 1)

This shows how, on the one hand, the system is trusted, by following the suggestions for next steps, although they are then critically assessed. While on the other hand, a distrust in the functionality of document generation and the reliability of the output leads to a manual take-over.

In addition, the code co-occurrence table (see Appendix D) indicates that codes such as *Constraint: Output Quality and Reliability* often appear together with *Constraint Workaround*, *Response Handling* and *Division of Labor: Human*. This suggests that perceived unreliability is typically handled through human reengagement and intensified checking, rather than leading to abandonment of AI.

These accounts underline that trust is not fixed but enacted situationally, anchored in task type, risk perception and prior experience.

4.3.4.2. *Data privacy, organizational responsibility and safe AI use*

Data privacy was a recurrent concern among participants and data privacy safeguards were frequently discussed during reflections and consistently enacted in practice. During the observations, data privacy safeguards, such as extracting sensitive information from prompts or using internal models to process sensitive data were frequently observed and often showed stabilization between rounds, which indicates that these practices were increasingly routinized rather than ad-hoc. The evolution matrices in Appendix E and the synthesized table in chapter 4.1 highlights this observation. An example of these practices and their consistency across rounds are the field notes for participant 7:

“Sensitive information is processed (sales numbers, customer info, etc.). Copilot in excel Copilot Agent with internal company integration used” (Participant 7, Observation Round 1)

“Deletes customer names and numbers out of data set before uploading into ChatGPT” (Participant 7, Observation Round 2)

As can be seen, during both observation rounds, adequate measures were taken by the participant to ensure data privacy safeguards when working with the AI system.

At the same time, however, one instance of a minor data privacy breach was observed with a customer name inserted in a prompt, illustrating that uncertainty and occasional misuse still occur, especially in early phases. These practices illustrate how sociomaterial constraints (privacy regulation, organizational policy) shape what is considered “safe” enactment of AI.

When reflecting on these practices, participants frequently described self-imposed safeguards and expectations regarding organizational governance. In sales, for example, participant 2 set clear boundaries regarding personal identifiable information:

“Whenever personal data are involved. I would never simply insert those. I would feel uneasy about that. Otherwise you always have to weigh up: what am I allowed to put in, what is intended for internal use and should not end up in the AI?” (P02, Interview, ¶53)

Personal data or other sensitive information are deliberately kept out of prompts. Whether data can be processed with the AI system from a data privacy standpoint requires careful consideration by the participant during enactment. This constant weighing of utility against privacy risk defines the boundary of the AI’s involvement in sensitive tasks and limits the extent of AI use cases.

Participant 5 similarly kept prices and internal company data out of prompts:

“I am reluctant to include prices or internal information in AI texts. I add that myself, I do not want to end up on thin ice. Some things I deliberately leave out. [...] In social media and marketing we are highly sensitized, because of end-user/customer data, photos, trademark rights and so on. I prefer to do too little rather than too much.” (P05, Interview, ¶62; ¶68)

Here, heightened sensitivity for data privacy safeguards was expressed by the participant. This risk-averse approach limits the scope of AI use to ensure compliance with data protection norms. The participant also revealed that the entire department is “*highly sensitized*” to Data Protection, indicating preliminary work by the organization in sharpening the focus on the topic.

Participant 3 expanded on the role of the organization in this regard, by noting that:

“Companies have a particular responsibility here to carry out regular awareness-raising” (P03, Interview, ¶163).

Thereby shifting the responsibility for safe practices from the individual employee towards the organization. Overall, the potential risk of data leaks that comes with using AI tools sharpened an often already present awareness for data protection measures, which in turn affects enactment practices and limits the scope of potential use cases.

4.3.4.3. *Reconfiguring expertise: Empowerment, deskilling, and the illusion of competence*

This theme captures the profound impact of AI on professional identity. Participants oscillated between feeling empowered by new capabilities and fearing the erosion of core skills or risks that come with supposed expertise.

On the one hand, AI functioned as a capability enhancer. Participant 5 noted that AI allows them to “*go deeper*” in blog posts, enabling more information-rich content. Participant 4 experienced several advantages that come with AI integration that led to overall higher quality content:

“I have more information in the text, and the posts no longer all sound similar. I can control tonality, that works very well. There is more variety. [...] Of course I look over it, but overall better than when I write alone.” (P04, Interview, ¶194–207)

Here, the AI empowered the participant to improve their work on several aspects, such as information richness, variety and quality of the content. Participants 1 and 6 described a form of empowerment, where AI enables them to bridge knowledge gaps and increase their expertise. On the one hand because the technology makes the user “*somewhat of an expert*” themselves (P01, Interview, ¶169) and by raising one’s expertise to then “*talk to the experts in a more targeted manner*” (P06, Interview, ¶126).

In both cases the technology was perceived to expand professional capability through access to synthesized knowledge. However, both participants also warned that this heightened expertise could be dangerous when visible output is decoupled from actual understanding. Both participants hinted at previous experiences where colleagues relied on or forwarded AI-generated outputs, which due to a lack of expertise were not validated, leading to a form of supposed expertise and potential misjudgments (see P01, Interview, ¶182 and P06, Interview, ¶132 in section 4.2.2.).

For other participants, the possibilities and ease of use for generative AI created anxiety about skill erosion. Participant 3 explicitly worried about losing the cognitive discipline required for knowledge work and becoming “*lazy*” (P03, Interview, ¶57). This fear articulates a potential trade-off where convenience of the technology comes at the cost of cognitive sharpness and competence.

These reflections reveal how AI is both a source of empowerment and a potential threat. Not only to reliable expertise, but also to professional identity and the competencies through which that identity is enacted. Consequently, AI integration does not merely augment task performance; it reconfigures how professionals understand, justify, and safeguard their own expertise in everyday work practices.

The fourth theme synthesized how participants negotiate trust in AI outputs, data privacy, professional identity and perceived capability loss. These tensions shape when and how AI is enacted and highlight the inseparability of social and material aspects of the routines.

4.4. Summary and Transition to Discussion

This chapter presented the findings from the observations and the interviews of the seven knowledge workers who participated in this study as well as the integrated findings from both data sources. Together, the findings reveal how generative AI is enacted in practice and how this affects work routines. Four themes were derived to explain this phenomenon.

Theme 1 captures the conceptual shift where knowledge workers redefine their relationship with technology, moving from viewing it as a passive instrument to a flexible collaborator. Rather than simply executing commands, the AI is often engaged in a cooperative dialogue and is entrusted with bounded cognitive subtasks like ideation, drafting or research, while humans retain the strategic framing of the activity. This transforms the enactment of work into a co-production process and enables tasks that were previously too resource-intensive to perform manually, thus expanding the scope of individual performances within work routines.

The second theme describes a structural transformation which follows from this enactment and is characterized by a layered workflow where human actors frame tasks, delegate execution to the AI, and reclaim control for final verification. As cognitively demanding work such as research or drafting texts is frontloaded to the AI, the human role shifts towards orchestration, rigorous oversight, and the retention of the “last word” to ensure accountability. Simultaneously, this structural efficiency leads to a social consolidation, in which tasks that previously required coordination with junior staff or external experts are absorbed into a self-contained human-AI dyad, insulating the workflow from broader organizational interaction.

While themes 1 and 2 describe how AI is enacted, Theme 3 explains the temporal evolution of these enactment practices. Effective integration is not immediate but learned through a transition from exploratory trial-and-error toward stabilized and proficient interactions with the technology. Over time, participants develop sophisticated prompting scripts and reusable templates. Thereby, shifting their efforts upstream, focusing on strategic task pre-structuring, where goals are clearly defined before engagement begins. As users navigate the system’s capabilities, they establish distinct tool ecologies by selectively adopting features that prove reliable while abandoning those that fail. This evolution from improvisation to routinization turns ad-hoc experiments into reliable, repeatable workflows and thus stabilizes the enactment structure.

Finally, this theme identifies the conditioning mechanisms that drive the behaviors observed in the previous themes. The rigorous verification in Theme 2 is necessary because trust in AI output is situational and negotiated output-by-output due to the system’s probabilistic nature. While participants value efficiency gains, they remain acutely aware of risks regarding accuracy and reliability, treating verification as a non-optional safeguard. Furthermore, the collaboration and expansion of actions described in Theme 1 creates tension regarding professional identity. Participants oscillate between feeling empowered by AI’s capabilities and fearing potential risks due to reliability issues. While the technology empowers workers by closing knowledge gaps, it simultaneously raises concerns that the convincing nature of AI outputs may mask a lack of underlying domain expertise

Together, these themes illustrate that integrating generative AI is a dynamic sociomaterial process rather than a static adoption event. While AI’s affordances enable delegation of subtasks and expansion of routine scope (Theme 1), its inherent constraints and risks compel a continuous negotiation of agency (Theme 4). This tension results in a specific enactment structure defined by rigorous human oversight and orchestration (Theme 2), which only stabilizes through learned practice and evolving strategies (Theme 3). Ultimately, the integration process represents an evolving human-AI imbrication, where agency is fluidly delegated and reclaimed to ensure the reliability of professional work. The following chapter builds on these insights to interpret their theoretical implications and provide practical guidance for organizational integration.

5. Discussion

The study set out to address the research gap identified in the introduction. Organizations struggle to understand how generative AI can be integrated into everyday work, and existing Information Systems models offer limited guidance because they conceptualize technology adoption as a one-time event or are grounded in technologies that differ fundamentally from generative AI. Building on the integrated findings presented in Chapter 4, this discussion chapter interprets what the observed enactments imply for theory and practice. It connects the empirical patterns to sociomateriality and routine dynamics, clarifies how generative AI becomes a technology-in-practice through repeated use, and explains why integration is best understood as an ongoing negotiation rather than a stable state of post-adoption.

The chapter proceeds as follows. Section 5.1 is organized around the three sub-research questions and develops theoretical implications by linking the findings to existing research and by qualifying assumptions in light of generative AI's unique properties. Section 5.2 derives practical implications for workflow design, training, governance, and organizational learning. Finally, section 5.3 outlines limitations of the study and proposes directions for future research.

5.1. Theoretical Implications

The theoretical implications of this study are twofold. First, the findings reinforce and extend sociomaterial perspectives and routine dynamics accounts of technology in organizations by providing fine-grained evidence on how generative AI becomes a technology-in-practice through situated enactment. Second, they challenge specific assumptions regarding the stability of sociomaterial entanglements, professional identity, and adoption as a discrete event, suggesting that generative AI requires a refinement of these concepts.

The first sub-question examined what use cases of generative AI can be identified in organizational work contexts and how work routines are defined. In this organization, generative AI is enacted primarily as a flexible collaborator capable of handling bounded cognitive subtasks such as ideation, exploratory research, summarization, and drafting text.

This aligns with Orlikowski's (2000) practice lens, which posits that technology structures are not inherent but emergent in use. In this study, the same underlying generative AI capability is enacted differently across routines, for example as a "research assistant" in compliance, a "creative partner" in marketing, or a "coder" in engineering. The significance of this finding lies not only in the variety of enacted roles, but in how use cases are defined through negotiated delegation boundaries. Participants delineate what can be offloaded to generative AI, for example producing a first draft, and what remains human-led, for example topic selection, strategic judgment, and accountability. For probabilistic generative AI, defining these boundaries is as consequential as recognizing capabilities, because the boundary marks where human judgment and responsibility are retained.

Table 6 summarizes the observed individual performances, the routines in which they are embedded, and the corresponding use case categories.

Table 6: Individual Performance, Routine and Business Use Case

Individual Performance	Routine	Business Use Case
Social Media post generation	Generating Marketing Content	Content Creation & Enhancement
Conduct research and write quotations for customer	Preparing Customer Quotations	Knowledge Management & Retrieval, Content Creation & Enhancement
Analyzing sales data	Monthly Reporting	Decision Support & Analysis
Research to create concept for product testing	Product development	Ideation & Brainstorming

Developing automated tool for product development	Product development	Process Automation & Task Augmentation
Creating compliance documents	Compliance Research	Compliance, Risk & Legal Support

Theoretically, these observations extend the practice lens by showing that generative AI is not experienced as a static tool with predefined effects. Instead, it is configured through prompting scripts, task definitions, interaction sequencing, and validation routines that stabilize what the system is allowed to do in a given routine (Orlikowski, 2000, 2002). The need to negotiate delegation boundaries foregrounds how enacted affordances and constraints jointly shape routine definitions. Constraints such as hallucinations, limited formatting and document-generation reliability, and data privacy risks do not merely accompany use. They actively delimit feasible enactments and influence which affordances are realized and which remain unrealized. This refines sociomaterial accounts by showing that, for generative AI, enacted roles are not only a matter of situated creativity but also a response to persistent uncertainty about output reliability and permissible data use.

The second sub question examined how knowledge workers enact generative AI within their work routines. The analysis indicates that enactment is not simple tool adoption, but an ongoing configuration of agency organized around conditional trust and supported by specific interaction styles.

A primary enactment pattern is a three-stage division of labor, which can be described as a **Sandwich Model**. In this configuration, the human actor frames the task (top layer), generative AI performs bounded production work such as drafting text or conducting exploratory research (middle layer), and the human actor reasserts control through verification, editing, and finalization (bottom layer). This structure is a sociomaterial consequence of how participants balance efficiency gains with perceived risk. Participants value the speed and generative capacity of the system while remaining skeptical of factual accuracy, formatting fidelity, and the general reliability of outputs. The Sandwich Model operationalizes this ambivalent trust stance by embedding generative AI's productive but unstable material agency within layers of human judgment and accountability.

Participants rely on generative AI as a productive collaborator, yet they also anticipate that it can be wrong, misaligned, or formatted in unusable ways. The Sandwich Model stabilizes this ambivalence by allocating trust selectively in the middle layer, while they withhold trust for factual correctness, contextual appropriateness, and accountability, which are protected through framing and verification. In this sense, the structure is not only a workflow choice but also a risk-management arrangement that translates conditional trust into stable workflows.

A different enactment pattern would likely shift both the distribution of effort and the kinds of breakdowns that occur. Removing any layer increases predictable failure modes, but it also reveals different organizational consequences. If the top framing layer was omitted or outsourced to generative AI, outputs would more often drift from local goals or become overly generic. This would increase downstream rework and thus make AI integration significantly less useful. If the bottom verification layer were minimized, the routine could become faster in the short term, but error propagation would become more likely. In low-stakes contexts this might be tolerated, yet in high-stakes contexts it would amplify exposure to hallucinations, outdated sources, and reputational risk. If the middle execution layer were reduced and generative AI were used only at the beginning for ideation, the organization would preserve human craftsmanship and control, but many of the observed productivity gains would be forfeited and the technology-in-practice would narrow to a creativity support tool. Conversely, if generative AI were positioned primarily at the end as an auditor or fact-checker, the enactment would assume a level of reliability that participants currently do not grant the system. This could produce a false sense of security if the audit itself is probabilistic and opaque, potentially shifting rather than eliminating risk.

These hypothetical alternatives underline why the observed sandwich structure is a plausible stabilization, as it captures the benefits of generative AI while keeping accountability, interpretive judgment, and risk containment anchored in human practice.

The conditional trust which leads to the Sandwich Model workflow structure also produces a **Volatile Boundary of Agency**. Unlike traditional divisions of work that remain comparatively stable, the findings indicate a boundary that shifts repeatedly within the same enactment. A user may delegate a full task (expanding the AI's agency), encounter a hallucination or functional failure and immediately reclaim the task (reasserting human agency), and then re-delegate refinement. The boundary is thus renegotiated line-by-line based on immediate model performance and human judgment. This observation provides a concrete mechanism for how sociomaterial imbrication unfolds with generative AI, not as a single shift from human to machine, but as repeated micro shifts within a task (D'Adderio, 2008; Leonardi, 2011; Orlikowski, 2007). This volatility challenges assumptions of stability embedded in many adoption models. Theories such as TAM or UTAUT typically operationalize adoption as relatively stable acceptance and use of technology's features. In contrast, these findings suggest that for generative AI, the boundary between what the human does and what the system does is not fixed once a tool is introduced. Instead, it is repeatedly negotiated during use through delegating, reclaiming, and re-delegating within a single task. In this sense, adoption may be better conceptualized as a fluid negotiation of agency rather than a stable state.

This continual negotiation requires users to draw on specific skills. First, verification and critical thinking are required to evaluate outputs and decide whether to accept, refine via generative AI, or revise manually, thereby realizing the bottom layer of the Sandwich Model. Second, clear goal specification and task alignment are required to guide the system toward acceptable outputs, thereby realizing the top layer. Together, these skills resemble supervisory work, namely framing tasks, monitoring performance, deciding when to intervene, and determining when to reclaim work. This suggests a shift in many roles from direct production toward orchestration of a capable but fallible assistant. Competence is thus demonstrated less through producing, for example, marketing text or code from scratch and more through the ability to frame tasks precisely and audit outputs rigorously.

This supervisory dynamic is reflected in interaction styles. Generative AI is frequently described in collegial terms and is sometimes attributed with personality. Co-writing unfolds in a pattern that mirrors collaboration with a junior colleague: the system proposes drafts or suggestions, and the human reads, critiques, and refines the output. This supports conceptualizations of AI as a collaborator rather than a passive tool and echoes conceptual work on AI as a counterpart in organizational settings (Anthony et al., 2023; Drossel & Löfgren Hallbeck, 2024).

The finding that the division of labor between human and generative AI is not stable but negotiated throughout enactment also challenges assumptions about stability in sociomaterial entanglements and professional identity. Sociomaterial research has shown how the entanglement of social expectations and material artifacts can reinforce stable identities. A prominent example is Orlikowski's (2007) analysis of the "*BlackBerry manager*" where device reliability and the social expectation of connectivity mutually reinforced an "*always-on*" identity. In that case, the stability of the entanglement was supported by the reliability of the material agency, because the device consistently enabled the expected behavior. Thus, an "*always-on*" manager is defined by always being reachable, because the affordance of the tool they are equipped with (E-Mails on the BlackBerry phone) reliably enables this identity.

In contrast, the **AI-Augmented Expert** observed in this study is characterized by conditional entanglement. Because generative AI is probabilistic and prone to hallucinations, the material agency can undermine the professional identity it appears to support. The worker is an AI-Augmented Expert only if they successfully enact the validation layer. When this condition is not met, the entanglement can collapse into the **Illusion of competence**. When verification is weak, AI-generated fluency can

appear authoritative while masking gaps in understanding, increasing the likelihood of uncritical forwarding or decision-making based on plausible but incorrect content. This implies that for probabilistic technologies, sociomaterial entanglements rely less on stable mutual reinforcement and more on continuous verification and risk management embedded in routine performance.

The third sub-question examined how enactment practices and work routines evolve over time. The longitudinal design with two observation rounds and retrospective reconstruction of pre-AI routines reveals gradual but significant shifts in micro practices and indicates that routines are structurally transformed through expansion and consolidation.

The findings show that, enabled by affordances of generative AI, routines expand through the introduction of new value-adding steps that were previously too resource-intensive. This indicates that the ostensive aspect of the routine, the abstract idea of what, for example, "good reporting" looks like, is being rewritten. In observed cases, generative AI raised the baseline for organizational output. What was once an extra feature is becoming a standard expectation because the cost of producing it has dropped. This supports the view of routines as generative systems where technology enables new ostensive patterns (Feldman & Pentland, 2003).

A more critical finding is the consolidation of social coordination. Tasks that previously required delegating work to trainees or consulting external experts are now contained within a dyadic Human-AI loop. While efficient, this insulation of the workflow bypasses traditional social learning mechanisms and reduces organizational interaction. The implication is not simply that individual routines become faster, but that routines may become less visible and less shared across the organization. As a result, opportunities for mentorship and knowledge sharing can diminish even as individual efficiency improves.

Finally, enactment practices evolve from exploration toward early stabilization of practices. In early stages, users relied on trial-and-error for prompting and feature use. Over the observation period, these practices matured into strategic task pre-structuring, selective feature adoption, and the use of prompt libraries. As users save and share prompt templates, they solidify the technology-in-practice with hard artifacts that make certain enactments repeatable. The move from trial-and-error to more targeted approaches show a form of stabilization as micro practices turn into reliable workflows, indicating a maturing adoption phase. This development is consistent with routine dynamics, where repeated performances generate more coherent ostensive patterns and stabilize expectations about "how we do this routine" (Feldman, 2000; Feldman & Pentland, 2003; Pentland & Feldman, 2005).

These temporal dynamics extend current debates about generative AI at work by specifying the micro-level mechanisms through which broader transformations unfold. Existing research has highlighted the transformative potential of generative AI for productivity, task allocation, and skill requirements (Felten et al., 2023; McAfee et al., 2023; Retkowsky et al., 2024). The present findings complement this work by showing how repeated performances with AI lead to changes in work practices, as well as the emergence of new routine steps or to the abandonment or delegation of others. They also show how routines can remain flexible and subject to continuous adjustment when hybrid failure points and trust issues persist, echoing the idea that routines are both sources of stability and change (Feldman et al., 2016; Pentland & Feldman, 2005).

In addition, these findings challenge assumptions of technology adoption as a one-time event present in traditional models such as TAM or UTAUT. Across the two observation rounds, enactments evolved in several cases from broad experimentation to more effective workflows for the same tasks, or to expanded application ranges entirely. This suggests that efficiency gains from generative AI integration may only manifest after an experimentation period in which users develop prompting scripts, application scenarios and task boundaries. For organizations, this implies that benefits require either deliberate space for practice development or substantial upfront work to assess the range of applications and the correct enactment practices before scaling adoption.

5.2. Practical Implications

The findings have several implications for organizations that seek to integrate generative AI into knowledge work and for the design of training and governance.

First, organizations can operationalize the observed Sandwich Model by translating the sequence of framing, generative AI execution, and human validation into explicit workflow steps. This can be achieved through process checklists and templates that specify, for recurring tasks, (1) what contextual inputs must be provided, (2) what the system is expected to produce, and (3) what verification actions are mandatory before outputs are used. Training materials and internal guidelines can further distinguish tasks that are suitable for delegation from those that should remain human-led, such as high-risk decisions, sensitive communication, and interpretation of complex analytics. A practical way to implement this is to define a task-risk taxonomy and embed it in guidelines, review checklists, and standard operating procedures. Tasks deemed unsuitable for generative AI involvement should be explicitly marked and communicated to mitigate reliability and compliance risks.

Second, organizations should invest in practice-oriented training that focuses on prompting proficiency, feature use and validation skills. Participants in the study learned effective prompting through trial-and-error, peer exchange, and personal experimentation. Structured training can accelerate this learning by using concrete exercises that teach workers how to specify roles, audiences, and constraints, how to apply stepwise prompting approaches, and how to exploit features such as model switching and agent modes where appropriate. Training should also make validation routines explicit and repeatable, including source checking, cross comparison with trusted sources, and awareness of biases. Because several of these practices are already in place among participants, organizations can codify them as good practice rather than presenting them as abstract principles. Given that participants learned through peer exchange, organizations should institutionalize prompt libraries so that effective prompts and task structures can be saved, shared, and refined, thereby supporting collective learning. Additionally, regular roundtables with key users from different departments can support the dissemination of best practices, for example prompting expertise throughout the organization.

Third, managers should monitor how generative AI reshapes social coordination around routines and should actively counteract unintended insulation. The consolidation of coordination into human and generative AI dyads can reduce informal learning opportunities. If junior tasks like research and drafting are automated, organizations should ensure that entry-level staff still receive opportunities to develop competence and contextual understanding. Implementation-oriented responses include creating deliberate occasions for joint review of generative AI-supported outputs, pairing less experienced employees with senior colleagues for validation and interpretation, and intentionally allocating developmental tasks rather than allowing them to disappear by default.

Fourth, the study underlines the importance of data privacy governance that is integrated into everyday enactment. Organizations need clear guidelines on what data is permissible in prompts and they should provide secure internal models or protected environments where sensitive data can be processed. To support routinization, these rules should be embedded where work occurs, for example through standardized prompt starters, default settings, and warning messages that remind users of data handling constraints during use. This reduces the gap between formal policy and routine performance.

Finally, organizations should address concerns about Illusions of Competence. Participants fear that AI-generated texts can give others an impression of expertise that is not backed by understanding, leading to potentially harmful decisions. Managers can mitigate these risks by fostering practices that require employees to articulate the reasoning behind AI-assisted decisions and by encouraging transparency, for example by making explicit when AI has been used in the production of outputs or analyses. These practices reinforce accountability and help ensure that the perceived quality of AI-supported output is matched by adequate verification and understanding.

5.3. Limitations and Suggestions for Future Research

Several study-specific limitations should be acknowledged when interpreting the findings. These limitations, as well as potential avenues for future research, which address them are presented in the following.

First, the study is situated in a single organization that is in an early phase of generative AI implementation. This context offers the advantage of observing enactments as they emerge, yet it also means that the routines and practices described here are shaped by the particular digital infrastructure, governance, and culture of this company. Other organizations may differ in their tool ecologies, regulatory environment, or AI strategies. The findings therefore illuminate how generative AI can be enacted in one context rather than how it is enacted everywhere. Future research could address this, by conducting a comparative case study across organizations and sectors. This would enrich understanding of how context shapes enactment, as different industries face distinct regulatory regimes, data sensitivities, and competitive pressures. Cross case analyses could explore how these factors influence decisions about which tasks to delegate to AI, how strongly data privacy constraints are enforced in practice, and whether consolidation of coordination into human-AI dyads is more pronounced in some settings than others.

Second, participants were purposively sampled as employees who have actively used generative AI in their work before. This focus is appropriate for studying enactment practices, yet it necessarily underrepresents non-users, resisters, or occasional users. As a result, the dynamics of rejection, avoidance, or mandated use remain outside the empirical scope. However, further research could deliberately include non-users or reluctant users and workers in roles where AI is formally prohibited. Such studies would shed light on alternative enactment trajectories, for example conscious resistance, avoidance, or silent use outside official channels.

Third, the longitudinal window covers two observation rounds approximately six weeks apart. This design makes it possible to trace early stabilization and the emergence or disappearance of practices, yet it does not capture long term stabilization and institutionalization. Moreover, the generative AI systems and models themselves evolve rapidly, which means that e.g. features available at the time of data collection may have changed or expanded since then or limitations and risks mentioned in the study are fixed. The analysis therefore only reflects a particular phase in the co-evolution of tools and routines. Future studies could extend the temporal horizon to examine how generative AI related routines evolve over longer periods and through multiple cycles of tool updates and organizational change. Multiyear longitudinal research could investigate whether early patterns of human last-word control persist, whether extra steps become institutionalized, and how organizations adapt their structures as generative AI becomes more deeply embedded.

Fourth, the analysis is explicitly guided by a practice and sociomaterial lens. Concepts such as agency shifts, affordances, constraints, and routine dynamics shaped the observational focus, coding scheme, and interpretation. This theoretical grounding is consistent with the research questions and with the argument that generative AI demands practice-based approaches. At the same time, it may have led to less emphasis on other perspectives, such as individual differences in technology acceptance or organizational level strategic considerations. The study thus provides one theoretically informed reading of the data rather than an exhaustive account of all possible interpretations. Future work could explore the phenomenon with another theoretical lens or delve more deeply into other aspects. As such, studies might examine the phenomenon from an organizational perspective and investigate the role of organizational culture and strategy or even from a societal perspective and explore broader debates about identity and professionalism in the age of generative AI.

Finally, the reliance on shadowing and semi structured interviews introduces the challenges of reactivity and reconstruction. Participants may behave somewhat differently under observation and retrospective accounts of pre-AI routines depend on memory. The research design mitigated these issues through

repeated observations of comparable tasks as well as triangulation of observation and interview data, yet some distortion cannot be excluded completely. Future research could overcome these limitations by employing other methods. For instance, a mixed method approach could link micro-level enactments to meso and macro-level outcomes. Thereby, quantitative and qualitative data could be combined, and process mining or log analysis could be linked with observation data to quantify how routine durations, error rates, or rework levels change when generative AI is integrated. Such designs could more reliably assess under which conditions efficiency gains are achieved, while still preserving the rich understanding of practice provided by qualitative data.

This chapter has examined the enactment of generative AI as a flexible collaborator that reshapes work routines through a renegotiated division of labor and evolving practices of trust and control. By conceptualizing adoption as an ongoing sociomaterial process rather than a discrete event, the analysis highlights the need for organizations to actively structure these emerging human-AI interactions. The following conclusion synthesizes these theoretical and practical insights, answers the overarching research question, and offers a final reflection on the future of generative AI in knowledge work.

6. Conclusion

This thesis aimed at investigating the integration of generative AI into organizational work, motivated by the research gap identified in the introduction. Despite the rapid diffusion of the technology and the strategic value to organizations, there remains limited empirical understanding of its practical application in organizational contexts. Further, existing theoretical models of technology adoption are ill-equipped to explain the integration of open-ended, non-deterministic systems like generative AI. Addressing this challenge, the study was guided by the overarching research question: *How do knowledge workers enact generative AI in their work routines and how do these enactments and routines evolve over time?* To answer this, a qualitative, longitudinal research design was adopted, using semi-structured interviews and observations to capture the micro-level performances through which this novel technology becomes embedded in practice. By drawing on the practice lens and sociomateriality, the analysis moved beyond traditional adoption models to reveal how generative AI becomes part of everyday work and the sociomaterial dynamics through which human actors and AI systems jointly reconfigure routines.

With regard to the first sub question, which asked what use cases of generative AI can be identified in organizational work contexts and how work routines are defined, the literature establishes that generative AI supports diverse organizational functions. These can range from content creation and ideation to knowledge retrieval and process automation. The findings show that generative AI is primarily enacted as a flexible collaborator for bounded cognitive tasks within knowledge work routines. Across sales, controlling, marketing, engineering and management assistance, participants integrated generative AI into work routines such as campaign preparation, monthly reporting, product development and compliance research. Within these routines, the technology is used for ideation, exploratory research, summarization, drafting of texts and explanations and, in some cases, data preparation or coding.

Work routines were defined as repetitive, recognizable patterns of interdependent actions comprising both abstract "ostensive" and concrete "performative" aspects. The results demonstrate that routine definitions are not static. The integration of AI can stretch the ostensive aspect of routines, enabling the inclusion of new value-adding steps, such as explanatory summaries, which were previously too resource-intensive to perform.

The second sub question examined how knowledge workers enact generative AI within their work routines. The study finds that knowledge workers manage the integration of AI through a distinct division of labor, which is best described as a Sandwich Model. In this configuration, human actors frame the task, delegate execution to AI, and subsequently reclaim control for validation and refinement. This structure arises from a negotiation of trust. While users value the generative capacity of the system, they remain wary of its reliability. Consequently, agency is not fixed but exhibits a volatile boundary, shifting line-by-line between human and machine based on the immediate quality of the output.

Further, participants consistently position the technology as a junior assistant, sparring partner or quasi colleague, which is reflected in conversational prompting styles and collegial metaphors during interaction. In practice, this results in human AI co-writing arrangements in which the model generates drafts, suggestions or structured overviews, and the human carefully reads, evaluates and refines the outputs. Enactment is therefore not a one-time act of adoption, but an ongoing negotiation of trust, control and risk in everyday work. Human actors rely on generative AI to accelerate tasks and broaden their scope of action, yet they counterbalance its unstable material agency through intensive checking, manual correction, selective delegation and deliberate data privacy safeguards. This layered configuration reconfigures expertise. Professional competence is no longer demonstrated only by producing content independently, but also by orchestrating human AI collaboration, deciding when to trust or override AI outputs and maintaining accountability for the overall result.

The third sub question focused on how enactment practices of generative AI and work routines evolve over time. The longitudinal observations and interviews show that participants move from exploratory play toward more stabilized enactment practices and strategic workflows, while the configuration of routines is gradually reworked. Over the observed period, participants developed "prompt libraries" and formalized their interactions, moving from reactive adjustments to proactive task pre-structuring.

At the level of routines, generative AI supports both expansion and consolidation. Some routines gain additional steps, such as explanatory summaries to accompany quantitative reporting, while others become more compact as previously distributed preparatory work is consolidated into a single human AI workflow. At the same time, hybrid failure points emerge when AI generated outputs do not meet quality, formatting or reliability expectations, prompting participants either to refine their prompting and validation strategies or to reclaim specific tasks from AI and perform them manually. Overall, enactment practices and routines evolved toward more mature and routinized forms of collaboration with generative AI, while ongoing adjustment and occasional resistance still remained.

Taken together, these sub conclusions provide a direct answer to the main research question. Knowledge workers enact generative AI in their routines by configuring it as a flexible, yet carefully supervised collaborator that performs bounded cognitive tasks, generates alternative formulations and structures information, while human actors maintain strategic guidance, verification and final responsibility. Through repeated performances, this configuration stabilizes into layered human AI workflows that shift sub tasks like research and first draft production to the system and concentrate human work in evaluation, integration and oversight. Therefore, generative AI becomes a technology-in-practice that not only accelerates existing tasks but also reshapes the routines that structure organizational work. It contributes to expanding ostensive understandings of what a routine comprises, consolidates dispersed tasks into integrated human AI workflows and raises expectations regarding output quality and speed. The resulting routines are sociomaterial assemblages in which human and material agencies are tightly intertwined and continuously renegotiated, rather than fixed roles that can be predefined at the moment of adoption.

In summary, the key findings demonstrate that generative AI does not enter organizational work as a neutral, deterministic tool. Instead, it reconfigures both tasks and professional roles in ways that are at once enabling and problematic. On the enabling side, it amplifies human capabilities by accelerating research, broadening ideation and enhancing textual and analytical outputs, and it allows workers to operate at a higher level of abstraction in their routines. On the problematic side, it introduces new tensions around trust, control, expertise and data privacy. The notion of a volatile boundary of agency captures how responsibility for shaping and evaluating outputs shifts back and forth between human and AI within a single enactment. The figure of the AI augmented expert highlights the ambivalent position of workers who experience both empowerment and a risk of deskilling or illusions of competence when highly polished outputs can be produced without fully engaging in the underlying reasoning. These patterns underline that generative AI integration is not only a matter of efficiency gains, but also a transformation of what it means to perform and be recognized as a competent professional in sociomaterial routines.

Methodologically, the study demonstrates the value of a qualitative, longitudinal and practice-oriented design for examining generative AI in organizational contexts. By focusing on individual performances of routines and combining shadowing with semi structured interviews, the analysis captures the situated micro practices through which generative AI is enacted, negotiated and gradually stabilized in everyday work. At the same time, several limitations qualify the interpretation of the findings. The study is situated in a single organization in an early implementation phase, which means the results reflect a particular context and temporal moment rather than the full diversity of generative AI enactments. Participants were purposively sampled as active users and early adopters, so forms of resistance, avoidance or mandated use remain outside the empirical scope. The longitudinal window of approximately six weeks captures an important, yet relatively early, phase in the co-evolution of

technology, people and routines. Finally, the analysis is explicitly guided by a practice and sociomaterial lens and relies on interview and observation data, which foregrounds aspects of the phenomenon while inevitably leaving others less visible.

Despite these limitations, the thesis offers several contributions to information systems research. It extends the practice lens by providing an empirically grounded account of how generative and non-deterministic technology becomes enacted as a flexible collaborator in knowledge work, rather than as a stable artefact that is simply adopted and then used. Further, it contributes to sociomateriality by illustrating how affordances, constraints and agency shifts around generative AI jointly drive routine change, making visible a fluid and sometimes fragile entanglement between human judgment and AI generated output. Also, it enriches routine dynamics research by showing how generative AI can both expand and consolidate routines, raise the baseline for what is considered a complete or good performance and potentially alter the pathways through which expertise is developed and recognized. Together, these contributions refine existing theories of technology in practice by highlighting the volatility, ambivalence and iterative nature of human AI collaboration in knowledge work.

The study also has implications for organizational practice, particularly for managers and practitioners who are responsible for integrating generative AI into everyday work. The findings suggest that organizations should consciously structure the human AI division of labor, clearly distinguishing tasks that can be safely delegated to generative AI from those that should remain human led, such as high-risk decisions, sensitive communication and interpretation of complex analytics. Practice oriented training that focuses on prompting proficiency, feature selection and safe enactment can help employees develop robust routines for working with generative AI, including strategies for verification and data protection. Managers should monitor how generative AI reshapes learning trajectories and mentoring relationships, since automating junior tasks risks narrowing opportunities for skill development if no alternative learning arrangements are established. Furthermore, governance frameworks need to address data privacy explicitly and support safe practices through technical safeguards and clear guidelines. Finally, organizations should respond to concerns about illusions of competence by fostering transparency about AI involvement in outputs and by encouraging employees to articulate their reasoning when relying on AI assisted results.

Building on these insights, the thesis points to several directions for future research. Longer term studies could trace how human AI routines develop over extended periods and how early enactment patterns stabilize, are abandoned or are reconfigured as generative AI becomes more deeply embedded in organizations. Comparative research across organizations, sectors and professional roles could examine how different institutional contexts, task structures and governance regimes shape decisions about which tasks to delegate to AI, how strongly data privacy constraints are enforced and when reliance on human AI dyads becomes more pronounced. Future work could also deliberately include non-users, reluctant users or those who engage in silent, unofficial use of generative AI in order to capture a broader spectrum of enactments and resistances. Mixed method designs that combine qualitative insights with quantitative measures of performance, quality or error rates could deepen understanding of how micro level enactments relate to organizational outcomes and how efficiency gains can be achieved without compromising trust or expertise. Finally, further qualitative studies could delve more deeply into the sociomaterial production of expertise in AI rich environments, exploring how professional identity, standards of competence and social signaling of expertise are reconfigured as generative AI becomes a routine part of knowledge work.

Overall, this thesis shows that integrating generative AI into organizational work is not a matter of simply adding a powerful new tool to existing routines. It is a sociomaterial process in which human actors and AI systems continually co-produce the patterns of action that constitute work and represents a profound shift in the texture of organizational practice. It transforms the worker from a sole creator into an orchestrator of artificial capabilities, demanding new forms of vigilance and engagement. By tracing how knowledge workers learn to collaborate with generative AI, how they negotiate trust and

control and how their routines evolve over time, the study offers a nuanced account of technology in practice at a moment when generative AI is rapidly diffusing into organizations. In doing so, it provides a foundation for scholars and practitioners to engage more deliberately with the opportunities and challenges of generative AI. As organizations continue to navigate this transition, success will depend not merely on deploying the technology, but on mastering the delicate and dynamic partnership between human judgment and machine generation.

Appendix

A Observation Guide

Category	Dimension	Observable Cue / Indicator (Look-fors)
<i>Routine</i>	Embedding environment	Which tools/platforms are visible (e.g., Teams, IDE, browser, plug-ins)?
<i>Routine</i>	Routine type	What routine is being performed?
<i>Routine</i>	Other artifacts	What additional materials are used (templates, notes, emails, docs)?
<i>Routine</i>	Division of labor	Which steps remain human-performed vs. delegated to the AI?
<i>Routine</i>	Integration	AI used at beginning, end, or throughout?
<i>Enactment</i>	Prompting	How are prompts/questions formulated?
<i>Enactment</i>	Data-privacy safeguards	Anonymization of sensitive information (e.g., customer names)?
<i>Enactment</i>	Feature use	Use of specialized tools (e.g., code, models)?
<i>Enactment</i>	Thread management	Start of new chat for new topic?
<i>Enactment</i>	Response handling	How are AI outputs checked, accepted, modified, or rejected?
<i>Sociomaterial Dynamics</i>	Agency shifts	Who/what moves the action forward at different points?
<i>Sociomaterial Dynamics</i>	Affordances	Which opportunities of the AI are taken up, ignored, or resisted?
<i>Sociomaterial Dynamics</i>	Constraints	Where do technological constraints block action?
<i>Temporal Aspects</i>	Stability vs. improvisation	Are practices routinized or improvised?
<i>Temporal Aspects</i>	Evolution	What new practices have emerged since the first observation?
<i>Temporal Aspects</i>	Disappearance	Which previous practices have faded or been abandoned?
<i>Notes</i>	Observer memos	Reflections on participant's proficiency, routinization, human-AI interaction and overall approach.

B Interview Questionnaire

Part 1. Warm-up / Context

1. Explain the purpose and conditions of the interview:
 - “Routine” is used as the central concept.
 - Recording will be processed anonymously and not published with names.
 2. Can you briefly describe your role and the types of tasks you most frequently perform?
 3. Recap of the observed task/routine:
 - Round 1: _____
 - Round 2: _____
→ Classification: _____
-

Part 2. Current Routine (Observed + Participant Perspective)

1. Would you say that you usually use AI in this type of routine, or only occasionally?
 2. Are there steps in this routine where you always use AI - things you typically delegate to AI?
 3. Are there parts of the task that you prefer to keep without AI? Why?
-

Part 3. Specific Observed Behaviors (Participant-Specific)

(Insert 2–3 cues from your observation notes here.)

1. _____
 2. _____
-

Part 4. Pre-AI Routine (Baseline)

1. Before you started using AI for [observed routine/task], how did you normally proceed?
 - What were the main steps?
 - Which tools or documents did you rely on?
 - Where did you invest the most effort or time?
 2. If no fixed routine existed:
 - “When you had to research for your work or solve a problem, how did you typically proceed before AI?”
-

Part 5. Changes in the Routine Through AI

1. Overall - what has AI changed in this task: the steps, their sequence, or who/what performs them?
 2. What benefits have you noticed compared to before?
 3. What challenges or risks have you noticed compared to before?
-

Part 6. Outlook

1. Do you think your way of working with AI in this task is now stable, or will it continue to evolve? / Will it become a fixed part of your routine, or not?
-

Closing

- “Is there anything I have not asked that you consider important regarding how this task has changed with AI?”

C Codebook

Code	Definition	Example Quote	Grounding
○ Adaptive Experimentation	Instances where participants mention experimentation for learning how to work with the AI system.	"people are slowly feeling their way forward to figure out how it works best."	3 (2)
○ Affordance	Captures potential ways the AI system can be used or engaged with. Can either be enacted or resisted, enabling certain actions and outcomes.		47 (7)
○ Affordance: Advanced Cognitive and Contextual Support	AI system's capacity to extend human cognitive capabilities by reasoning over complex problems or memorizing context.	"model seems to understand specifications for "facebook" and adjusts tonality accordingly"	12 (7)
○ Affordance: AI suggested next Steps	AI system's capacity to provide ideas for next steps or advice for further action.	"Participant picks up "advice" from the model and asks it to incorporate this advice for the next version."	15 (7)
○ Affordance: Automation Enacted	AI system's capacity to automate entire steps. Instances where an affordance is enacted by the participant.	"participant first tried to edit document himself then lets ChatGPT creates word document for download"	19 (6)
○ Affordance: Not Enacted	Instances where an affordance is resisted by the participant.	"Uses gpt 4.1 model specifically to analyze data set"	26 (7)
○ AI Integration: Beginning	Indicates if AI system was used in the beginning of the observation.	"Final word document created manually."	11 (5)
○ AI Integration: Middle	Indicates if AI system was used in the middle of the observation.	"Starts task by writing prompt. "	12 (6)
○ Cooperative Dialogue	Instances when participants formulate prompts like a dialogue or almost like talking to a human.	"mainly used in the middle"	8 (5)
○ AI-led Action	AI system initiates next step, indicating agency. A factor of the AI system that limits or restricts the possible actions of a participant.	"Use of "please" within prompts"	9 (4)
○ Constraint: Functional Failures	Constraints regarding the general functionality of AI systems.	"Initial analysis done with suggested prompts"	10 (6)
○ Constraint: Logical and Reasoning Limitations	Constraints regarding logic and reasoning capabilities of AI systems.		42 (7)
○ Constraint: Memory and Context	Constraints relating to previous information or context window size.	"Participant asks model to create document but it is not created in output"	7 (4)
○ Constraint: Output Quality and Reliability	Constraints relating to output quality.	"It becomes difficult when the AI is supposed to build on information I have already worked out or follow my line of thought. That's where a language-based model reaches its limits."	2 (2)
○ Constraint: Performance / Processing	Constraints regarding processing or duration of output generation.	" Participant has to upload earlier generated document again after AI fails to access it ("file not available")"	3 (3)
○ Constraint Experienced	Instances where a constraint is experienced by a participant, leading to irritation or no further steps.	"Tries different variants of prompts when output not suitable"	29 (7)
○ Constraint Workaround	Instances where a constraint of the AI system leads to a (manual) workaround of the participant.	"Visible dissatisfaction with duration of output generation"	3 (3)
○ Critical Evaluation and Verification Skills	Instances where participants mention learning critical evaluation or verification skills through working with AI.	"Visible dissatisfaction observed when output not as expected or error message occurred"	17 (7)
○ Data Privacy Safeguard	Observed or mentioned instances of data privacy safeguards kept.	"Participant merges excel sheets manually after model failed to do so"	20 (7)
○ Data Privacy Safeguard breached	Observed or mentioned instances of data privacy safeguards breached.		
○ Delegated to AI	An action or task is deliberately delegated to AI, indicated either by a shift of division of labor between round 1 and 2 or by participant mention.	"we've trained ourselves (my colleague and I) to take a critical look and to check things multiple times."	2 (1)
○ Delegation Decision	Rationales for deciding to delegate an action to AI or keeping it with the human.	"Deletes customer names and numbers out of data set before uploading into chatgpt"	10 (6)
○ Delegation Decision: Based on Affordance	Participant mentions delegating task to AI because of realized affordance.	"Customer name copied and pasted into copilot"	1 (1)
		"That is now done faster by the AI"	14 (5)
		"Now the AI, with relatively little effort ... delivers a good, concise overview of the analyzed data and charts"	29 (7)
			3 (3)

<ul style="list-style-type: none"> ○ Delegation 	Participant mentions doing a task or step manually to keep control or incorporate creativity.	"Even if I run a text through two different AI versions, it still ends up with my personal touch."	5 (3)
<ul style="list-style-type: none"> Decision: Based on Control / Creativity ○ Delegation 	Participant mentions doing a task or step manually for a lack of knowledge how AI could offer support.	"Maybe also because I don't know how it would work."	1 (1)
<ul style="list-style-type: none"> Decision: Based on Lack of Experience ○ Delegation 	Participant mentions doing a task or step manually or delegating it to AI based on complexity.	"I would say: For very simple questions, I don't necessarily use the AI."	11 (5)
<ul style="list-style-type: none"> Decision: Based on Task Complexity ○ Delegation 	Participant mentions doing a task or step manually for trust and reliability reasons.	"...whenever personal data is involved. I would never just enter that as it is. I'd feel uneasy about it."	10 (6)
<ul style="list-style-type: none"> Decision: Based on Trust / Reliability ○ 	Behaviors/practices which were present in round 1 of the observations but not in round 2.		11 (5)
<ul style="list-style-type: none"> Disappearance / Abandonment ○ Division of Labor: AI ○ Division of Labor: 	Task or step is primarily executed by the AI system.		40 (7)
<ul style="list-style-type: none"> Collaborative / Shared ○ Division of Labor: Human 	Task or step is not primarily executed by the AI system or the human but collaboratively.		8 (5)
<ul style="list-style-type: none"> ○ Emergence of New Practices ○ Final Edit by Human 	Task or step is primarily executed by the human.		58 (7)
	Behaviors which were not present in round 1 of the observations but in round 2.		17 (6)
	Instances where the participant conducts the final edit of an output.	"Participant edits output manually and makes adjustments"	12 (6)
	Captures the clear role separation between human and AI between steering a task and assisting.	"My idea remains the foundation. AI is a supplement/improvement to what the human brings to the table."	2 (2)
<ul style="list-style-type: none"> ○ Human steers - AI assists ○ Knowledge Sharing and Peer Learning ○ Maintained Human Control ○ New Step Added 	Mentions of peer learning and knowledge sharing.	"My colleague is very skilled; she sent me a note with her prompts. We support each other and benefit from one another."	1 (1)
	An action or task is deliberately kept under human control and not delegated to AI.	"But I check everything afterwards."	15 (6)
	Additional step added between rounds or indicated by participant.		15 (7)
	Outlook of future AI integration, use cases or routine change.	"The more you use it, the greater the relief and time savings - why not get some help? I want to keep integrating it (AI) further."	11 (7)
<ul style="list-style-type: none"> ○ Outlook ○ Perceived Capability Enhancement ○ Perceived Efficiency / Productivity ○ Perceived Quality or Outcome Change ○ Perceived Risk 	Participants perceive capability enhancement through AI integration.	"I'd normally need an expert. With AI, I can to some extent become capable myself."	7 (6)
	Participants perceive productivity or efficiency gains through AI integration.	"The processing time is much shorter."	21 (6)
	Participants perceive increased output quality through AI integration.	"Also, there's more information in the text now, and the posts don't all sound the same anymore"	9 (6)
	Participants perceive general increased or additional risks through AI integration.	"I have an underlying feeling that I might be losing some competence ..."	8 (5)
	Participants perceive increased risk for incorrect information through AI integration.	"But AI sometimes talks nonsense, too. Sometimes the mistakes are easy to spot, sometimes they're harder. Especially if you're not an expert in the field, there's a risk of being misled."	3 (3)
<ul style="list-style-type: none"> ○ Perceived Risk: Incorrect Information ○ Perceived Risk: Supposed Expertise 	Participants perceive increased risk for supposed expertise through AI integration.	"AI can make people believe they're more competent than they actually are."	2 (2)
<ul style="list-style-type: none"> ○ Post-AI 	Indicating observations or mentions regarding routine after AI integration.		78 (7)
<ul style="list-style-type: none"> ○ Pre-AI 	Indicating observations or mentions regarding routine before AI integration.	"That only came up with the introduction of AI."	17 (7)
	Observations of participants engaging with the AI system through prompts.	"before, we used to consult many more experts, internally or externally. Depending on the topic: service providers, training organizations, occupational associations"	56 (7)
<ul style="list-style-type: none"> ○ Prompting: Basic ○ Prompting: Clear Goal ○ Prompting: Context Given 	Observed prompting without advanced methods.	"No role framing"	9 (5)
	Observed prompting with goal specification.	"Specifies output within prompt"	7 (5)
	Observed prompting with context information provided.	"Screenshot with product information"	4 (3)

○ Prompting: Explorative	Observed prompting in an explorative manner.	"Multiple trial and error attempts"	3 (2)
○ Prompting: Extensive	Observed prompting extensive.	"Detailed description of task used for initial prompt"	11 (6)
○ Prompting: Iterative	Observed prompting iterative.	"Iterative prompting to refine result"	12 (6)
○ Prompting: Pre-made prompts	Observed use of pre-made prompt templates.	"Pre-made prompt used."	1 (1)
○ Prompting: RAG	Observed prompting with direct reference to sources.	"product website linked in prompt for context."	4 (2)
○ Prompting: Role Framing	Observed prompting with role explanation.	"Use role framing ("I am a controller...")"	4 (3)
○ Prompting: Short	Observed prompting short.	"Prompt rather short, level of detail limited."	3 (2)
○ Prompting: Variant		"Asks model to generate multiple options and then picks best parts of each option to create final one"	6 (5)
Exploration	Observed prompting for different variants. Mentions of participants improving their prompting proficiency through learning and skill development.	"At the beginning, you feel your way into it and try out what comes out. Little by little, you learn how to phrase prompts so that the answers fit."	9 (4)
○ Prompting Proficiency		"Downloaded document does not match requirements then, code is further refined using the model and then copied into the document"	11 (4)
○ Reclaimed by human	Task or step which was first delegated to AI but then reclaimed by the human.		
○ Response Handling	Observations of participants engaging with the output of an AI system.		44 (7)
○ Response Handling: check sources	Participant is observed checking the sources of output.	"Checks sources and reads through material thoroughly."	7 (4)
○ Response Handling: compared to other model	Participant is observed comparing the output of two models.	"compares outputs of both models to the same prompt"	6 (4)
○ Response Handling: compared to trusted source	Participant is observed comparing the output to a trusted source.	"Compares llm output with excel sheet to validate numbers"	5 (3)
○ Response Handling: manual edit	Participant is observed manually editing the output.	"Participant edits output manually and makes adjustments"	10 (6)
○ Response Handling: output used directly	Participant is observed using the output without checks or modifications.	"Output code used directly from the model"	3 (2)
○ Response Handling: thorough manual check	Participant is observed thoroughly checking the output manually.	"Descriptive: Participant reads output thoroughly and assesses it"	12 (6)
○ Response Handling: tool used to check for viruses	Participant is observed using a specialized tool to check the output. Indicating certain steps or tasks within the underlying routine.	"Created documents checked for viruses using specialized software on computer"	2 (1)
○ Routine Step			113 (7)
○ Routine Step: Code Generation	Captures instances where participants create, modify, or generate programming code or scripts.		2 (1)
○ Routine Step: Coordination with Colleague	Captures instances where participants exchange information, align expectations, or coordinate actions with colleagues to progress within a shared workflow or task.		5 (4)
○ Routine Step: Data Analysis	Captures instances where participants examine, interpret, or manipulate quantitative or qualitative data to extract insights, identify patterns, or inform subsequent steps.		3 (1)
○ Routine Step: Document Generation	Captures instances where participants produce structured written outputs, such as reports, summaries, briefs, or other formal documents.		10 (3)
○ Routine Step: Formatting / Output Preparation	Captures instances where participants refine, format, or prepare outputs for presentation or delivery by adjusting layout, style, structure, or other display-oriented elements.		8 (5)
○ Routine Step: Ideation / Brainstorming	Captures instances where participants develop, explore, or generate new ideas, concepts, or approaches.		10 (4)
○ Routine Step: Image Generation	Captures instances where participants create or refine visual content or images.		2 (1)

○ Routine Step: Information Search / Research	Captures instances where participants seek, collect, or review information from internal or external sources.		16 (6)
○ Routine Step: Text Draft Generation	Captures instances where participants produce initial written content or textual drafts.		13 (4)
○ Routine Step: Text Refinement	Captures instances where participants edit, improve, or adjust existing text to refine clarity, correctness, structure, or quality.		16 (6)
○ Routine Step: Validation / Verification	Captures instances where participants check, confirm, or validate information, outputs, or decisions to ensure correctness, accuracy, or compliance with requirements.		17 (7)
○ Routine Step: Visualize Data	Captures instances where participants create or refine visual representations of data, such as charts, graphs, or dashboards, to support understanding or communication.		3 (1)
○ Stabilization ○ Stabilized Workflow Pattern	Behavior which had been observed in round 1 of observations and round 2. Mentions that a certain behavioral or workflow pattern has become routinized.	"Nowadays I use AI all the time"	69 (7) 24 (7)
○ Step Removed / Automated	Step that had previously existed but was removed from the routine or fully automated.		5 (4)
○ Strategic and Contextual Awareness	Mentions of learnings by participants regarding strategic application of AI.	"By now, I first think without ChatGPT: What do I even want? Otherwise you can quickly get a bit lost"	7 (3)
○ Thread Management	Observations of participant's engagement with the thread interface of the AI system.		15 (7)
○ Thread Management: Consistent	Participant keeps consistent topic per thread.	"Descriptive: Opens new chat before starting first task"	12 (7)
○ Thread Management: Inconsistent	Participant does not keeps consistent topic per thread.		3 (3)

D Code Co-occurrence Tables

Table 7: Routine Step & Division of Labor (Filtered by Post-AI)

	○ Routine Step: Code Generation Gr=2	○ Routine Step: Coordination with Colleague Gr=6	○ Routine Step: Data Analysis Gr=3	○ Routine Step: Document Generation Gr=5	○ Routine Step: Formatting / Output Preparation Gr=9	○ Routine Step: Ideation / Brainstorming Gr=7	○ Routine Step: Image Generation Gr=2	○ Routine Step: Information Search / Research Gr=14	○ Routine Step: Text Draft Generation Gr=13	○ Routine Step: Text Refinement Gr=15	○ Routine Step: Validation / Verification Gr=16	○ Routine Step: Visualize Data Gr=3
○ Division of Labor: AI Gr=36	2	0	2	3	0	2	1	9	8	6	0	1
○ Division of Labor: Collaborative / Shared Gr=8	0	0	0	0	0	0	0	0	1	6	0	0
○ Division of Labor: Human Gr=50	0	0	0	2	8	4	0	0	2	1	16	1

Table 8: Response Handling per Participant

	P01 Gr=59; GS=3	P02 Gr=64; GS=3	P03 Gr=56; GS=3	P04 Gr=64; GS=3	P05 Gr=57; GS=3	P06 Gr=52; GS=3	P07 Gr=52; GS=3	SUM
○ Response Handling: check sources Gr=9	2	1	3	1	2	0	0	9
○ Response Handling: compared to other model Gr=5	3	0	0	0	1	0	1	5
○ Response Handling: compared to trusted source Gr=5	0	1	0	1	0	0	3	5
○ Response Handling: manual edit Gr=10	1	1	2	3	2	0	1	10
○ Response Handling: output used directly Gr=3	0	0	0	1	0	2	0	3
○ Response Handling: thorough manual check Gr=14	0	2	3	4	2	2	1	14
○ Response Handling: tool used to check for viruses Gr=2	0	0	0	0	0	2	0	2

	○ Affordance: Advanced Cognitive and Contextual Support Gr=12	○ Affordance: AI suggested next Steps Gr=15	○ Affordance: Automation Gr=19
○ Affordance Enacted Gr=26	7	10	8
○ Affordance Not Enacted Gr=11	2	4	5

E Evolution Matrices from Observations Per Participant

Table 9: Evolution Matrix for Participant 1

	Round 1	Round 2	Changes
Observed Activity	Conducts research to create test scenario for engineering of a product	Research to optimize product input & description on website	Different activity. Both activities part of overarching routine of “product development”
AI Interface	ChatGPT Chat Interface Copilot Chat Interface	ChatGPT Chat Interface	Copilot dropped. Same Interface mode
Routine Structure & Division of Labor	AI integrated in the beginning of observation. AI: Research and text generation. Human: <ul style="list-style-type: none"> • Validation of output • document generation. 	AI integrated in the beginning of observation. AI: Research and text generation. Human: <ul style="list-style-type: none"> • Validation of output • document generation. 	Stabilized Routine Structure & Division of Labor
Prompting	Extensive prompts are used that include contextual information and rely on basic prompting techniques. The same prompt is entered into both Copilot and ChatGPT, after which the outputs are compared. Prompts frequently include polite formulations such as the use of “please.” The participant iteratively refines the output with follow-up prompts.	Extensive prompts are used that include contextual information and incorporate role framing and retrieval-augmented generation. The first prompt is started with “hi...” Output is adjusted with multiple follow-up prompts.	Extensive and iterative prompting has stabilized and interaction with the system shows anthropomorphizing tendencies. More sophisticated prompting techniques have emerged over time, while the earlier practice of variant exploration has disappeared.
Response Handling	Checks the sources provided in the output and manually edits the final version. The outputs of two different models (chatgpt and copilot) are compared and then combined or the more suitable one taken.	The final output is manually edited and the sources are checked.	Thorough validation is carried out consistently, while the use of two different models has disappeared.
Other Enactment Practices	Stays in same chat per topic and no sensitive information is used in prompts.	Stays in same chat per topic and no sensitive information is used in prompts.	Thread management and data privacy safeguards have stabilized.
Affordances	Follows AI suggested next steps multiple times. But does not use document generation functionality	Follows AI suggested next steps multiple times. Document generation functionality not used, instead manually creates document and copies output.	Following AI suggested next step and not using the document generation functionality have stabilized.
Constraints	Dissatisfaction with output of Copilot multiple times.	Model “forgets” information during task.	Constraints persistent although of different type. Use of copilot has disappeared in round two potentially due to dissatisfaction with results.

Table 10: Evolution Matrix for Participant 2

	Round 1	Round 2	Changes
Observed Activity	Preparing Customer Quotations	Preparing Customer Quotations	Same activity
AI Interface	Copilot Chat Interface	ChatGPT Chat Interface	Same Interface mode
Routine Structure & Division of Labor	AI integrated in the beginning. AI: <ul style="list-style-type: none"> • Research • Text generation Collaborative/Shared: Text refinement Human: Validation/Verification	AI integrated in the beginning. AI: <ul style="list-style-type: none"> • Research • Idea Generation • Text generation • Document generation 	Additional steps added to the activity and delegated to AI.

		Collaborative/Shared: Text refinement Human: Validation/Verification	
Prompting	Short prompts with no role framing or more advanced method. Output is iteratively refined with follow-up prompts. When output does not meet requirements, trial and error prompting is used for adjustments.	Pre-made prompts are used, incorporating role framing and more sophisticated prompting techniques.	Prompting practices develop toward more sophisticated forms and less iterative refinement.
Response Handling	Sources are checked, the output is reviewed thoroughly, and the final version is manually edited.	Sources are checked and the output is reviewed thoroughly.	Thorough validation and source checking are carried out consistently.
Other Enactment Practices	The interaction remains within the same chat per topic, and no sensitive information is used in prompts.	The interaction remains within the same chat per topic, and no sensitive information is used in prompts.	Stabilized Thread management and data privacy safeguards
Affordances	No suggested next steps by model followed or any other additional affordances besides text generation used.	Different models are used for different steps, e.g. thinking vs. “normal” model. The agent mode feature is employed to retrieve information from websites. No suggested next steps proposed by the model are followed.	Additional affordances enacted. Next steps suggested by model are consistently and deliberately not followed.
Constraints	Hallucination was observed when product-specific information was retrieved. Participant had to manually adjust output.	Output generation takes long time and is not in specified format. Participant then has to manually adjust output.	Constraints persistent in both rounds and lead to manual adjustments each time

Table 11: Evolution Matrix for Participant 3

	Round 1	Round 2	Changes
Observed Activity	Compliance Research	Compliance Research	Same activity
AI Interface	Copilot Chat Interface	Copilot Chat Interface	Same Interface mode
Routine Structure & Division of Labor	AI integrated in the beginning. Division of Labor AI: <ul style="list-style-type: none"> • Research • Text generation Collaborative/Shared: Text refinement Human: <ul style="list-style-type: none"> • Text draft generation • Validation/Verification • Document generation and output formatting 	AI integrated in the beginning. Division of Labor AI: <ul style="list-style-type: none"> • Research • Text generation • Document generation Collaborative/Shared: Text refinement Human: <ul style="list-style-type: none"> • Validation/Verification • Document generation and output formatting 	Additional steps delegated to AI Document generation reclaimed by human after model fails
Prompting	Short and basic prompts with no advanced prompting techniques. Output is further refined with iterative prompting.	Short and basic prompts are used, followed by iterative refinement and variant exploration of different outputs.	Prompting behavior has stabilized, while variant exploration has emerged in second round
Response Handling	The output is reviewed thoroughly and sources are checked. The final version is manually copied to a word document and edited there.	The output is reviewed thoroughly, and the final version is manually copied to a word document and edited there after the AI failed to generate the document.	Final manual editing and thorough checking have stabilized.

Other Enactment Practices	The interaction remains within the same chat per topic, and no sensitive information is used in prompts.	The interaction remains within the same chat per topic, and no sensitive information is used in prompts.	Stabilized Thread management and data privacy safeguards
Affordances	Suggested next steps proposed by the AI are followed, while the document generation functionality is not used.	Suggested next steps proposed by the AI are followed several times, and the document generation functionality is used in the end although unsuccessfully.	More affordances taken up in addition to the persistent following of AI-suggested next steps.
Constraints	Unsatisfied with model's formulation on several occasions, leading to manual adjustments by the human.	Document generation by LLM fails and then human has to do it manually.	Constraints persist, leading to manual override by human.

Table 12: Evolution Matrix for Participant 4

	Round 1	Round 2	Changes
Observed Activity	Generating Marketing Content	Generating Marketing Content	Same activity
AI Interface	ChatGPT Chat Interface	ChatGPT Chat Interface	Same Interface mode
Routine Structure & Division of Labor	AI integrated in the beginning. Division of Labor AI: Text draft generation Collaborative/Shared: Text refinement Human: <ul style="list-style-type: none"> • Validation/Verification • Ideation / Brainstorming 	AI integrated in the beginning. Division of Labor AI: Text draft generation Collaborative/Shared: Text refinement Human: <ul style="list-style-type: none"> • Validation/Verification • Ideation / Brainstorming 	Consistent structure and division of labor
Prompting	Extensive prompts are used that include a link to a website for contextual information. A pre-configured custom GPT is used, which has been prompted for the specific task. And iterative refinements of outputs take place within a single chat.	Extensive prompts are used that include target group specifications, links, and tone markers. A pre-configured custom GPT is used, and outputs are iterative refined with follow up prompts.	The use of a custom GPT and iterative prompting has stabilized, and prompts have become more specific and goal oriented.
Response Handling	The output is checked thoroughly, and the final version is manually edited and rewritten.	The output is checked thoroughly, and manual edits are limited to small stylistic adjustments (e.g., tone, emojis, brand terminology).	Thorough checks remain, while manual edits become slightly less profound.
Other Enactment Practices	No sensitive information entered in prompts and stays within one chat for multiple tasks.	No sensitive information entered in prompts and stays within one chat for multiple tasks.	Stabilized Thread management and data privacy safeguards
Affordances	A customized GPT specialized for this activity is used, and no suggested next steps proposed by the model are followed.	A customized GPT specialized for this activity is used, and no suggested next steps proposed by the model are followed.	Affordances are used consistently.
Constraints	None observed	None observed	No changes

Table 13: Evolution Matrix for Participant 5

	Round 1	Round 2	Changes
Observed Activity	Generating Marketing Content	Generating Marketing Content	Same activity
AI Interface	ChatGPT Chat Interface	ChatGPT Chat Interface	Same Interface mode
Routine Structure &	AI integrated in the beginning. Division of Labor AI: Text draft generation	AI integrated in the beginning. Division of Labor AI:	Additional steps added (research and image

Division of Labor	Collaborative/Shared: Text refinement Human: <ul style="list-style-type: none"> • Validation/Verification • Ideation / Brainstorming • Output formatting 	<ul style="list-style-type: none"> • Research • Text draft generation • Image generation • text refinement Human: <ul style="list-style-type: none"> • Validation/Verification • Ideation / Brainstorming 	generation) and delegated to AI
Prompting	Detailed prompts are used that include contextual information, relying on basic prompting techniques.	Detailed prompts are formulated in a conversational manner (“you know our target customers”), relying on basic prompting techniques while using a customized GPT. Outputs are iteratively refined with follow-up prompts.	Prompting shifts from directive, task-specific formulations toward a more conversational style that embeds shared context. The use of a custom GPT has emerged in round 2.
Response Handling	The generated output and the provided sources are checked thoroughly, and the final version is manually edited by the participant.	The output is refined with minimal rewriting, a thorough check is conducted without checking sources, and the AI output is accepted with stylistic adjustments only.	Thorough checks persist, but manual edits become less profound.
Other Enactment Practices	New chat for each topic started No sensitive information used in prompts	Stays within same chat for multiple tasks but specifies (“new task”) No sensitive information used in prompts	Thread management awareness inconsistent Data privacy safeguards stabilized
Affordances	Follows AI suggested next steps for several adjustments. Document generation functionality not used.	Suggested next steps proposed by the AI are followed several times. A customized GPT is used, and the image generation feature of the AI system is employed.	Previously used affordances have stabilized. Image generation and customized GPT have been added.
Constraints	None observed	None observed	No changes

Table 14: Evolution Matrix for Participant 6

	Round 1	Round 2	Changes
Observed Activity	Programming automatic document generation	Programming internal company platform	Different activities
AI Interface	ChatGPT Chat Interface	ChatGPT Chat Interface	Same Interface mode
Routine Structure & Division of Labor	AI integrated in the beginning. Division of Labor AI: <ul style="list-style-type: none"> • Code generation • Document generation • Code refinement Human: <ul style="list-style-type: none"> • Validation/Verification • Document generation 	AI integrated in the beginning. Division of Labor AI: <ul style="list-style-type: none"> • Code generation • Document generation • Code refinement Human: <ul style="list-style-type: none"> • Validation/Verification • Document generation 	Stabilized structure and division of labor
Prompting	Prompts are rather detailed but contain no advanced prompting techniques such as role framing. Output is iteratively adjusted, when unsatisfactory and refined with multiple follow-up prompts.	Basic prompts are used that include a high level of detail. Then, follow-up prompts are used to refine the output.	Basic prompting and iterative adjustment has stabilized.
Response Handling	The output is initially used directly without manual edits, a tool is used to check the created document for viruses, and the final output is manually edited after the AI-generated output did not work.	The output is checked thoroughly through manual reviews.	Output check became more thorough.

Other Enactment Practices	No sensitive information is used in prompts and the participant stays with the same topic per thread.	No new chat started for new task	Thread management became inconsistent
Affordances	Suggested next steps proposed by the model are followed, the model is used to create the document, and different models are used for different steps, e.g. reasoning model for structuring task and then “normal” model.	Suggested next steps proposed by the model are followed and the model is used to create a document. Different models and features are used for different steps, e.g. reasoning model and agent mode.	Use of multiple affordances is consistent between rounds.
Constraints	AI-generated documents do not meet the specified requirements, after which manual edits are carried out by the human.	The AI does not create the document when prompted, requiring the human to create it manually, and output generation takes a long time.	Constraints in both rounds shape activity and lead to manual adjustments.

Table 15: Evolution Matrix for Participant 7

	Round 1	Round 2	Changes
Observed Activity	Monthly Sales Reporting	Monthly Sales Reporting	Same activity
AI Interface	Copilot Chat Interface Copilot Excel Integration	Chat GPT Chat Interface	Copilot in excel dropped
Routine Structure & Division of Labor	AI integrated in the middle. Division of Labor AI: Data Analysis & Visualization Human: Validation/Verification	AI integrated in the middle. Division of Labor AI: <ul style="list-style-type: none"> Text Generation Data Analysis & Visualization Human: <ul style="list-style-type: none"> Data Analysis & Visualization Validation/Verification 	AI delegated data analysis and visualization experimentally tried with AI, but then reclaimed by human. Text generation as new step is added and delegated to AI.
Prompting	Extensive prompts are used with detailed instructions and role framing, and trial-and-error prompting is applied when results do not match expectations.	Extensive prompts are used with detailed instructions and role framing. Output is refined multiple times with follow-up prompts.	Prompting behavior has stabilized, shifting from improvised trial-and-error prompting toward a more stable pattern.
Response Handling	Copilot is used simultaneously via the chat interface and the Excel integration, and the results are compared. Numbers in the output are checked against the underlying data set, and the output is manually edited and refined in the end.	Numbers in the output are compared against the data set, and the output is checked thoroughly with few manual edits applied to the text.	Use of two models and comparison of the outputs has disappeared. Thorough manual checks and comparison of critical information such as sales figures has stabilized.
Other Enactment Practices	Sensitive information processed with internal model only. New chat is opened and existing chat deleted when a new step is started.	No sensitive information used in prompts, customer names or other sensitive data is anonymized before processing. A new chat is opened each time a new step starts.	Stabilized consistent thread management and data privacy safeguards
Affordances	Use of a specialized copilot agent for data analysis. Suggested next Steps and initial prompts provided by model are followed several times.	Use of different models for different tasks, e.g. specific GPT model with higher token limit for large data processing.	Use of specialized Copilot agent is abandoned, while the use of specialized functionality persists.
Constraints	Multiple error messages occur when using Copilot in Excel, and output generation takes a long time.	Dissatisfaction with the output leads to iterative refinement or manual edits.	Constraints persistent

F Field Notes Example

- **Participant ID:** 5
- **Role:** Social Media Manager
- **Observed Activity:** Social media post generation
- **Routine label:** Generating marketing content
- **Observation round:** R1
- **Date:** 12.06.2025
- **Start–End:** 15:30–16:40
- **Duration:** 70 min
- **Setting:** Office; one colleague present in the room (just working nearby, no interaction relevant to task observed).
- **Artefacts visible/used:** ChatGPT in browser, Microsoft Word, product website

Category	Dimension	Descriptive notes (R1)
Routine	Embedding environment	Two screens. ChatGPT open in a browser tab when the observation starts. Word open on the other screen.
Routine	Routine type	Works on two deliverables back-to-back: marketing text for a Facebook post, then a product description sheet in word.
Routine	Other artifacts	Mostly moves between ChatGPT and Word. Product website is used as context information in prompt via link and to access information. No other documents clearly visible.
Routine	Division of labor	Participant sets the goal of the task, writes prompts, validates output, and does the final wording and formatting in Word. ChatGPT produces draft text and rewrites when asked (shorter, different tone, etc.).
Routine	Integration	ChatGPT is used from the start and then repeatedly during the process: prompt → output → follow-up prompt → copy into Word → manual edits → back to chat for another rewrite.
Enactment	Prompting	Starts task by writing prompt to generate text. Prompts are phrased as direct instructions (e.g., “create a marketing text for Facebook...”). Model seems to understand specifications for "facebook" and adjusts tonality accordingly. Participant adds plenty of detail and constraints and includes the product website link for context. Output clearly specified in prompt. Then iterative refinement of output with follow-up prompts. Follow-ups are short and concrete (e.g., “make it shorter...”). Use of “please” and “thank you” in prompts. No explicit role framing in prompt observed. Model addresses participant by name.
Enactment	Data-privacy safeguards	Company name and product name appear in the prompt. No customer names or personal data observed.
Enactment	Feature use	Standard chat interface only. No visible use of add-ons or other models.
Enactment	Thread management	New chat is opened when topic changed.
Enactment	Response handling	Participant thoroughly analyses output and makes manual adjustments. Copies text into Word and edits manually. Also pastes text back into ChatGPT for another rewrite. Checks product details by looking back at the product website.

Sociomaterial dynamics	Agency shifts	Participant initiates task and drives the process. Suggestions for next steps by model followed several times. Participants assess outputs and then iterative refinement based on assessment of participant. Final edit and re-write done by participant.
Sociomaterial dynamics	Affordances	AI is mainly used for drafting text and iterative refinement. Model seems to understand how to fit a “Facebook” tone, suggesting previous configuration. Suggested next steps by model frequently followed.
Sociomaterial dynamics	Constraints	No tensions observed. Participant seems visibly content with model answers throughout observation.

Time-Ordered Activity Trace (Approximation)

- **15:30-15:35:** ChatGPT already open. Word open on second screen. Participant begins task setup.
- **15:35-16:05 (Task 1):** Facebook marketing text. Initial prompt → reads output → follow-up prompts for refinement → manual edits → copies into Facebook interface.
- **16:05-16:35 (Task 2):** Product data sheet. Starts a new chat thread → Prompts for creating a product description and marketing text based on product info from website → iterates → cross-checks against product website → copies into Word → manual edits.
- **16:35-16:40:** Final clean-up edits in Word and formatting. Session ends.

Analytic memo:

The participant appears quite routinized in using the model, both in the general interaction and for this specific routine. The collaboration between participant and ChatGPT looks smooth and well-aligned with clear roles: the participant sets the idea and goal via prompts, the model generates the text, participant reviews the output and then iterates quickly with short follow-ups. There are also signs of trust in the model’s capabilities, e.g., following suggestions forward, but this is paired with thorough checking and validation. The interaction also looks like the model is somewhat personalized/pre-configured (e.g., it addresses the participant by name and seems to pick up the expected tone for “Facebook” when prompted to do so). Starting a new chat between tasks also seems like a deliberate way to keep topics/context separated.

G Interview Transcript Example

Interviewer 0:06

I've started the recording – is that okay for you? Thanks again for taking the time. I'll ask you a few questions about the observations and the routine in general.

Participant 0:12

Yes, that's fine.

Interviewer 0:23

Maybe we'll start with you briefly describing your role and which tasks you handle most often.

Participant 0:37

I am a social media manager and also responsible for online and marketing content. I write texts – mainly in German – of different lengths, target groups, and text types: from press releases to social media texts to data sheets and website texts. For that, AI is very practical because you can “tune” it to different target groups, tones, and speech styles.

Interviewer 1:18

Thank you. About the observations: In round 1 you created marketing texts for a product and then a data sheet. In round 2 they were blog posts with a short preliminary research to narrow down the topic. The underlying routine is the creation of marketing material. Do you always use AI for that, occasionally, or rather rarely?

Participant 2:01

It's becoming more and more frequent and intensive – and the use changes the more you work with it. I often go deeper into topics, engage more with text structure and strategy. But you can also work off a lot “more superficially” when it comes to routine. For blog posts that are meant to convey knowledge and spark interest, it's helpful to go deeper – AI supports that.

Interviewer 3:03

So you already use AI very frequently – and that will likely increase further?

Participant 3:10

Yes, definitely.

Interviewer 3:18

Are there steps you always do with AI – and others that you deliberately do yourself?

Participant 3:25

I always do the finalizing myself. Even if I run a text through two AI variants, it still gets my personal touch at the end. I don't always agree with the AI, sometimes I know that something else would be better.

Participant 3:46

What I almost always do is run drafted texts through an AI for correction or ‘rounding off’, to see where I stand and what can be improved. The text creation can also happen without AI – I “write something off my chest” and then get the fine-tuning. I have the final word.

Interviewer 4:26

Is that because you want to keep control – or so that it sounds like you?

Participant 4:31

Both.

Interviewer 4:39

Have you always handled it that way, or because of bad experiences?

Participant 4:40

It can happen that a text goes through and I say, “Fits like that.” But mostly I round it off again. For press releases I add certain points myself (e.g. prices) and enter them into the form. I do the finish – that might change at some point, who knows.

Interviewer 5:25

Is that also because the AI lacks internal knowledge (prices/templates)?

Participant 5:30

Exactly. I am reluctant to include prices or internal information in AI texts. I add that myself, I do not want to end up on thin ice. Some things I deliberately leave out.

Interviewer 5:54

So also a data protection issue?

Participant 5:56

Always. In social media and marketing we are highly sensitized, because of end-user/customer data, photos, trademark rights and so on. I prefer to do too little rather than too much

Interviewer 6:28

About the observations: In round 2 AI seemed even more deeply integrated – additionally through a preliminary research.

Participant 6:59

Yes, exactly.

Interviewer 7:01

Is it becoming apparent that you increasingly integrate pre- and post-steps with AI alongside text creation?

Participant 7:11

Definitely. I'm also practicing with image generation, diagrams, etc. You constantly discover new things – and there are always new offerings. That won't end anytime soon.

Interviewer 7:40

Do you try things out and adopt them if they work? Does that work out often, or do you discard a lot?

Participant 7:46

I have different needs – one tool isn't equally good for everything. I use various versions. One example is a GPT called "Write for me," a strong writing assistant for editing. Downside: we work in a large team in ChatGPT – I have my niche, but it's not perfectly tailored to me. "Write for me" is, however, a "supercharged writing assistant" and helps a lot.

Interviewer 8:58

So versatile with new features/custom GPTs.

Interviewer 9:12

I noticed that in round 2 the manual editing was somewhat reduced – even though you want to keep the final touch.

Participant 9:25

Yes.

Interviewer 9:28

Do you nevertheless notice that you have to do less manually overall – because the results are getting better?

Participant 9:38

I'm walking a fine line there. Sometimes there are texts where I think: 'I could not have done it more beautifully', then I do not have to do anything. Sometimes I think: 'Wrong movie, absolutely not.' Then I finish it myself or mix two suggestions. I can't yet pinpoint why that is. Optimal is, of course, when it comes out exactly as I imagine it – that also happens.

Interviewer 10:15

Same routine, but sometimes it works, sometimes not?

Participant 10:20

Maybe topic-dependent – or my expectation is different. You learn every week; next week it can already look different again.

Interviewer 10:47

If the result fits, it's fine – you don't insist on always doing everything yourself?

Participant 10:56

Exactly. It has to match my gut feeling. That happens more and more often – but sometimes not at all. Similar to image generation.

Interviewer 11:19

Last observation: It seemed like close collaboration between you and ChatGPT – personalized ("Hello [name] ..."). You said things like: "You know our target group, right? Now write this text."

Participant 11:28

Yes.

Interviewer 11:35

Do you perceive that as collaboration – or rather as a tool?

Participant 11:53

It's a tool. But I enjoy using it as a "personality" – for me it's a "he." For whatever reason.

Interviewer 12:07

That differs – for some "she," for some "he."

Participant 12:07

For me, it's a 'he.' I find it easier to phrase things when I communicate 'on a buddy basis' – he understands that. I could also just type lists, but it's easier for me to 'chatter away.'

Interviewer 12:34

So like explaining to a colleague – and then comes the result?

Participant 12:35

Exactly. And when I notice, "Stop, I meant it differently," I correct. The responses are often very personal ("Have a nice afternoon," "See you tomorrow"). Nice – but it remains a tool.

Interviewer 13:14

How did the routine (marketing texts) work before AI? What were the main steps?

Participant 13:37

Example blog post (e.g. recipe: regional/seasonal): choose idea, test/cook recipe, take photos, write down recipe. Based on that, develop a story in my head and write the text.

By now, AI often takes over idea generation. We have enough ideas, but AI brings great, current suggestions that I can directly pass on as tasks ("Research ...," "Write a proposal about ..."). For example: "Baking paper in the air fryer – pros/cons." The research without AI takes significantly longer.

Also recipes: I refer to a product and ask for "3 quick recipes for student kitchens – why is the product practical for that?" That saves time. There will still be own recipes, but for more general topics AI is great – especially for knowledge sharing, because nothing gets forgotten. You can dig deep for a long time – that saves enormous time.

Interviewer 16:11

Without AI: rough research, script/outline, then write it out?

Participant 16:21

Yes.

Interviewer 16:28

Which tools before? And where was the greatest effort?

Participant 16:30

Google and Word. The greatest effort: building a coherent story out of the collected material. Now I can query trends and current things ("most popular summer dishes," etc.) – I get more input/opportunities.

Interviewer 17:08

So more possibilities, faster/more efficient – also better result?

Participant 17:17

Similar – I wasn't bad before either. But you can go deeper and offer more information. Accuracy is important to me; I use, for example, Perplexity instead of Google and have source references – I see where something comes from. More knowledge with less effort.

Interviewer 18:06

What new challenges/risks do you see?

Participant 18:15

Getting sidetracked: you go deeper and deeper, at some point far away from the actual goal. On the screen you can get lost.

Interviewer 18:31

It becomes too extensive – you lose the topic?

Participant 18:34

Yes, exactly. You have too much knowledge and want to include everything – no one wants to read that. The balance is important. That's tool usage – you have to work on and learn it.

Interviewer 19:02

The advantage "more information" can therefore also be a disadvantage.

Participant 19:14

Yes. You have to keep asking yourself: What is the aim of the article?' Focus on that, then it will work.

Interviewer 19:18

And that's your role – to manage that and keep the frame?

Participant 19:33

Yes, exactly.

Interviewer 19:40

Looking ahead: It already seems very integrated and routine. Will that go even deeper – more collaboration or delegation to AI?

Participant 20:11

I wouldn't mind automations – for that you have to dig deeper. For everyday posts/newsletters a certain automation would be helpful to process "side work" faster/easier. It will certainly go in that direction.

Interviewer 20:49

Exciting. Thank you – I'll stop the recording.

Participant 20:56

Yeah.

References

- Anthony, C., Bechky, B. A., & Fayard, A. L. (2023). “Collaborating” with AI: Taking a System View to Explore the Future of Work. *Organization Science*, 34(5), 1672–1694. <https://doi.org/10.1287/orsc.2022.1651>
- Baker, J. (2012). The Technology–Organization–Environment Framework. In Y. K. Dwivedi, M. R. Wade, & S. L. Schneeberger (Eds.), *Information Systems Theory: Explaining and Predicting Our Digital Society* (Vol. 1, pp. 231–245). Springer. https://doi.org/10.1007/978-1-4419-6108-2_12
- Becker, M. C. (2004). Organizational routines: A review of the literature. *Industrial and Corporate Change*, 13(4), 643–677. <https://doi.org/10.1093/icc/dth026>
- Bick, A., Blandin, A., & Deming, D. J. (2024). *The Rapid Adoption of Generative AI*. <https://doi.org/10.20955/WP.2024.027>
- Brachman, M., El-Ashry, A., Dugan, C., & Geyer, W. (2024, May 11). How KnowledgeWorkers Use and Want to Use LLMs in an Enterprise Context. *Conference on Human Factors in Computing Systems - Proceedings*. <https://doi.org/10.1145/3613905.3650841>
- Brown, S. (2025, June 2). *Machine learning and generative AI: What are they good for in 2025?* | MIT Sloan. <https://mitsloan.mit.edu/ideas-made-to-matter/machine-learning-and-generative-ai-what-are-they-good-for>
- Brynjolfsson, E., Li, D., Raymond, L. R., Acemoglu, D., Autor, D., Axelrod, A., Dillon, E., Enam, Z., Garicano, L., Frankel, A., Manning, S., Mullainathan, S., Pierson, E., Stern, S., Rambachan, A., Reenen, J. Van, Sadun, R., Shaw, K., & Stanton, C. (2023). *Generative AI at Work*. <http://www.nber.org/papers/w31161>
- Burton-Jones, A., & Grange, C. (2013). From Use to Effective Use: A Representation Theory Perspective. *Information Systems Research*, 24(3), 632–658. <https://doi.org/10.1287/isre.1120.0444>
- Burtsev, M., Reeves, M., & Job, A. (2024). The Working Limitations of Large Language Models. *MIT Sloan Management Review*, 65(2), 1–5. <https://sloanreview.mit.edu/article/the-working-limitations-of-large-language-models/>
- D’Adderio, L. (2008). The performativity of routines: Theorising the influence of artefacts and distributed agencies on routines dynamics. *Research Policy*, 37(5), 769–789. <https://doi.org/10.1016/j.respol.2007.12.012>
- Davis, F. D., & Granić, A. (2024). *The Technology Acceptance Model 30 Years of TAM*. Springer Nature Switzerland AG.
- DeepSeek-AI, Guo, D., Yang, D., Zhang, H., Song, J., Zhang, R., Xu, R., Zhu, Q., Ma, S., Wang, P., Bi, X., Zhang, X., Yu, X., Wu, Y., Wu, Z. F., Gou, Z., Shao, Z., Li, Z., Gao, Z., ... Zhang, Z. (2025). *DeepSeek-R1: Incentivizing Reasoning Capability in LLMs via Reinforcement Learning*. <http://arxiv.org/abs/2501.12948>
- Deloitte. (2023a). *A CEO’s guide to envisioning the Generative AI enterprise Leading a Generative AI-fueled enterprise: A CEO series Deloitte Global CEO Program Deloitte AI Institute TM*. www.deloitte.com/us/ceo
- Deloitte. (2023b). *Generative AI and the future of work The potential? Boundless*. www.deloitte.com/us/AIInstitute
- Deloitte. (2025). *Deloitte’s State of Generative AI in the Enterprise Quarter four report*.

- Drossel, M., & Löfgren Hallbeck, F. (2024). *Generative AI, the new colleague?-a sociomateriality perspective on the human-AI relationship* [Master Thesis]. University of Gothenburg.
- Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koochang, A., Raghavan, V., Ahuja, M., Albanna, H., Albashrawi, M. A., Al-Busaidi, A. S., Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., ... Wright, R. (2023). Opinion Paper: “So what if ChatGPT wrote it?” Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management*, 71, 102642. <https://doi.org/10.1016/j.ijinfomgt.2023.102642>
- Feldman, M. S. (2000). Organizational Routines as a Source of Continuous Change. *Organization Science*, 11(6), 611–629. <https://doi.org/10.1287/orsc.11.6.611.12529>
- Feldman, M. S., & Pentland, B. T. (2003). Reconceptualizing Organizational Routines as a Source of Flexibility and Change. *Administrative Science Quarterly*, 48(1), 94–118. <https://doi.org/10.2307/3556620>
- Feldman, M. S., Pentland, B. T., D’Adderio, L., & Lazaric, N. (2016). Beyond routines as things: Introduction to the special issue on routine dynamics. *Organization Science*, 27(3), 505–513. <https://doi.org/10.1287/ORSC.2016.1070>
- Felten, E. W., Raj, M., & Seamans, R. (2023). Occupational Heterogeneity in Exposure to Generative AI. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.4414065>
- Feuerriegel, S., Hartmann, J., Janiesch, C., & Zschech, P. (2023). Generative AI. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.4443189>
- Fui-Hoon Nah, F., Zheng, R., Cai, J., Siau, K., & Chen, L. (2023). Generative AI and ChatGPT: Applications, challenges, and AI-human collaboration. In *Journal of Information Technology Case and Application Research* (Vol. 25, Issue 3, pp. 277–304). Routledge. <https://doi.org/10.1080/15228053.2023.2233814>
- Glaser, V. L. (2017). Design Performances: How Organizations Inscribe Artifacts to Change Routines. *Academy of Management Journal*, 60(6), 2126–2154. <https://doi.org/10.5465/amj.2014.0842>
- Glaser, V. L., Valadao, R., & Hannigan, T. R. (2021). Algorithms and Routine Dynamics. In M. S. Feldman, L. D’Adderio, K. Dittrich, & P. Jarzabkowski (Eds.), *The Cambridge Handbook of Routine Dynamics* (pp. 324–339). Cambridge University Press. <https://doi.org/10.1017/9781108993340.024>
- Grattafiori, A., Dubey, A., Jauhri, A., Pandey, A., Kadian, A., Al-Dahle, A., Letman, A., Mathur, A., Schelten, A., Vaughan, A., Yang, A., Fan, A., Goyal, A., Hartshorn, A., Yang, A., Mitra, A., Sravankumar, A., Korenev, A., Hinsvark, A., ... Ma, Z. (2024). *The Llama 3 Herd of Models*. <http://arxiv.org/abs/2407.21783>
- Hafermalz, E., & Seymour, M. (2016). *Hello Computer: Towards a Research Agenda for Conceptualising “Presence” in Human-Computer Engagement*. <https://www.researchgate.net/publication/315486278>
- Howard-Grenville, J. A. (2005). The persistence of flexible organizational routines: The role of agency and organizational context. In *Organization Science* (Vol. 16, Issue 6, pp. 618–636). <https://doi.org/10.1287/orsc.1050.0150>
- Laskar, M. T. R., Alqahtani, S., Bari, M. S., Rahman, M., Khan, M. A. M., Khan, H., Jahan, I., Bhuiyan, A., Tan, C. W., Parvez, M. R., Hoque, E., Joty, S., & Huang, J. (2024). *A Systematic*

- Survey and Critical Review on Evaluating Large Language Models: Challenges, Limitations, and Recommendations*. <http://arxiv.org/abs/2407.04069>
- Lee, Y., Kozar, K. A., & Larsen, K. R. T. (2003). The Technology Acceptance Model: Past, Present, and Future. *Communications of the Association for Information Systems*, 12. <https://doi.org/10.17705/1CAIS.01250>
- Leonardi, P. M. (2011). When Flexible Routines Meet Flexible Technologies: Affordance, Constraint, and the Imbrication of Human and Material Agencies. *MIS Quarterly*, 35(1), 147–167.
- Leonardi, P. M. (2013). The Emergence of Materiality within Formal Organizations. In *How Matter Matters: Objects, Artifacts, and Materiality in Organization Studies*. Oxford University Press. <https://doi.org/10.1093/acprof:oso/9780199671533.001.0001>
- McAfee, A., Rock, D., & Brynjolfsson, E. (2023). How to Capitalize on Generative AI. *Harvard Business Review*.
- Minaee, S., Mikolov, T., Nikzad, N., Chenaghlu, M., Socher, R., Amatriain, X., & Gao, J. (2025). *Large Language Models: A Survey*. <http://arxiv.org/abs/2402.06196>
- Orlikowski, W. J. (2000). Using Technology and Constituting Structures: A Practice Lens for Studying Technology in Organizations. *Organization Science*, 11(4), 404–428. <https://www.jstor.org/stable/2640412>
- Orlikowski, W. J. (2002). Knowing in practice: Enacting a collective capability in distributed organizing. *Organization Science*, 13(3), 249–273. <https://doi.org/10.1287/orsc.13.3.249.2776>
- Orlikowski, W. J. (2007). Sociomaterial practices: Exploring technology at work. *Organization Studies*, 28(9), 1435–1448. <https://doi.org/10.1177/0170840607081138>
- Orlikowski, W. J., & Scott, S. V. (2008). 10 Sociomateriality: Challenging the Separation of Technology, Work and Organization. *The Academy of Management Annals*, 2(1), 433–474. <https://doi.org/10.1080/19416520802211644>
- Pentland, B. T., & Feldman, M. S. (2005). Organizational routines as a unit of analysis. In *Industrial and Corporate Change* (Vol. 14, Issue 5, pp. 793–815). Oxford University Press. <https://doi.org/10.1093/icc/dth070>
- Retkowsky, J., Hafermalz, E., & Huysman, M. (2024). Managing a ChatGPT-empowered workforce: Understanding its affordances and side effects. *Business Horizons*, 67(5), 511–523. <https://doi.org/10.1016/j.bushor.2024.04.009>
- Rosen, P. (2023, March). *AI Is on the Brink of an “iPhone Moment” and \$15 Trillion Impact: BofA - Markets Insider*. <https://markets.businessinsider.com/news/stocks/artificial-intelligence-ai-chatgpt-iphone-moment-bank-america-bofa-markets-2023-3>
- Scott, S. (2025, April 25). *How Generative AI Will Impact the Future of Work | Workday US*. <https://blog.workday.com/en-us/how-generative-ai-will-impact-the-future-work.html>
- Taylor, S., & Todd, P. A. (1995). Understanding Information Technology Usage: A Test of Competing Models. *Information Systems Research*, 6(2), 144–176. <http://www.jstor.org/stable/23011007>
- Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision Sciences*, 39(2), 273–315. <https://doi.org/10.1111/j.1540-5915.2008.00192.x>

- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*, 27(3), 425–478. <https://doi.org/10.2307/30036540>
- Venkatesh, V., Walton, S. M., Thong, J. Y. L., & Xu, X. (2012). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. In *MIS Quarterly* (Vol. 36, Issue 1). <http://ssrn.com/abstract=2002388>
- Wessel, M., Adam, M., Benlian, A., Majchrzak, A., & Thies, F. (2025). Generative AI and its Transformative Value for Digital Platforms. *Journal of Management Information Systems*, 42(2), 346–369. <https://doi.org/10.1080/07421222.2025.2487315>
- Yang, J., Jin, H., Tang, R., Han, X., Feng, Q., Jiang, H., Zhong, S., Yin, B., & Hu, X. (2024). Harnessing the Power of LLMs in Practice: A Survey on ChatGPT and Beyond. *ACM Transactions on Knowledge Discovery from Data*, 18(6). <https://doi.org/10.1145/3649506>
- Yoo, Y. (2010). Computing in Everyday Life: A Call for Research on Experiential Computing. *MIS Quarterly*, 34(2), 213–231. <https://doi.org/10.2307/20721425>
- Zhang, C., Zhang, C., Li, C., Qiao, Y., Zheng, S., Dam, S. K., Zhang, M., Kim, J. U., Kim, S. T., Choi, J., Park, G.-M., Bae, S.-H., Lee, L.-H., Hui, P., Kweon, I. S., & Hong, C. S. (2023). One Small Step for Generative AI, One Giant Leap for AGI: A Complete Survey on ChatGPT in AIGC Era. *ArXiv Preprint ArXiv:2304.06488*.