Navigating Generative AI Usage Tensions in Knowledge Work: A Socio-Technical Perspective

Research Paper

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Abstract. The integration of Generative Artificial Intelligence (GenAI) into knowledge work has sparked a complex interplay of advantages and challenges that organizations must navigate. This paper explores the tensions associated with the use of GenAI in knowledge work, focusing on the conflicting aspects of productivity, reliability, and data privacy using the socio-technical systems theory (STS). Through a systematic literature review and qualitative interviews with 18 knowledge workers, we identify tensions such as the productivity-reflection tension and the availability-reliability tension. We propose solutions, including human-in-the-loop models and robust AI governance policies to address these challenges, aiming to foster responsible GenAI usage that enhances efficiency while ensuring ethical standards and data protection.

Keywords: Generative AI, Knowledge work, Tensions, Socio-technical systems theory.

1 Introduction

Work is piling up on your desk. You remember that you need to review applications by tomorrow to fill the accountant position. Since you don't have much time and you need a quick result, you upload all the application documents to ChatGPT, enter a prompt on the selection criteria and you get a detailed and elaborate report on each applicant and even a recommendation on whom you should hire. And that's it. You have in mind that there are requirements for the input of personal data in ChatGPT, but since you don't have the time, you ignore them.

This situation above describes a *tension* in the use of Generative Artificial Intelligence (GenAI). In this context, tension emerges as a situation in which two or more opposing or conflicting forces occur simultaneously and in conflict with each other (Brooks et al. 2020). Tensions often arise when a change or innovation - in the context of our paper, the *adoption and use of GenAI* - brings both benefits and challenges, and organizations or users are required to navigate the competing aspects (Hietala et al. 2024). Today, GenAI has found its way into organizations, most prominently through the introduction and widespread adoption of ChatGPT. ChatGPT is a Large-Language Model (LLM) that generates different types of data (e.g., pictures, music, or text) based on an underlying set of training data, which, in turn, gives the perception of creativity (Banh and Strobel 2023; Wang et al. 2023). Given the transformative nature of GenAI for creative tasks, we find that it is potentially highly interesting in Information Systems (IS) research and practice in *knowledge work*. Knowledge work encompasses professions that rely on cognitive skills such as critical thinking, problem-solving, and information processing, including roles in journalism, law, and software development (Drucker 1999). Recent papers have found positive and negative application scenarios. For instance, GenAI has been shown to increase efficiency in content creation and software development but also raises concerns about originality, job displacement, and over-reliance on machine-generated outputs (Ritala et al. 2024). In journalism, AI-generated articles can significantly reduce the workload but may compromise journalistic integrity (Gutiérrez-Caneda et al. 2024). Similarly, in legal professions, LLMs can expedite contract analysis, but they pose risks regarding legal accountability and misinformation (Surden 2019).

Using GenAI can help simplify more error-prone and time-consuming tasks, such as generating source code, freeing users to perform more knowledge-intensive tasks that require more human input (Henkenjohann and Trenz 2024). At the same time, IS research shows that the increased use of technology can lead to the development of habits that lead to inaccurate use and blind reliance on the content that is generated (Söllner et al. 2024). This can have serious consequences not only for the user but also for the organization, for example, mishandling private data (Wagner et al. 2020).

Since knowledge work is characterized by autonomy, cognitive complexity and high demands on the integrity of information (Davenport 2005; Newell et al. 2009), academia serves as a prototypical context for investigating the use of GenAI, where tensions such as data ethics, authorship and accountability are particularly evident (Davison et al. 2023). It is therefore important to understand the tensions and find solutions so that the use of GenAI is purposeful for users and the company. We use a *dialectical inquiry* lens, which is, generally spoken, the study of oppositional forces, to capture these tensions (Ciriello and Mathiassen 2022). Accordingly, we want to answer the following research questions:

RQ1: *What are the tensions in GenAI use in organizational knowledge work?*
RQ2: *What are the responses to tensions in GenAI use in organizational knowledge work?*

To answer our research questions, we conducted a systematic literature review to identify tensions in GenAI use. To add a distinct practice perspective, we performed a qualitative interview study with 18 *knowledge workers* to understand user and organizational perspectives on tensions in GenAI use. Our work contributes to both theory and practice. From a theoretical perspective, we use the socio-technical systems theory (STS) to demonstrate the role and importance of tensions in GenAI use from both user and organizational perspectives. In other words, with our work, we can better explain how tensions change the work routines of knowledge workers and provide implications on how to resolve them to make the use of GenAI more sustainable and safer from an organizational perspective. From a practitioner perspective, we can provide insights into how to make the use of GenAI effective and safe, and present solutions to the tensions we identified that can help organizations establish GenAI-based work routines.

The remainder of our paper is structured as follows. After motivating our papers' research gap and presenting our goal, we provide insights into related work about knowledge work in the context of GenAI. Furthermore, we provide input on STS and its role in GenAI. We close the second chapter with insights about tensions. Afterward, we present our two methodological approaches and continue with a presentation of our results. Our paper closes with contributions for research and practices as well as limitations, an outlook for future research, and a conclusion.

2 Background

2.1 GenAI in Knowledge Work

GenAI can produce text, video, audio, images, and even code (Wang et al. 2023), unlike traditional AI, which typically focuses on specific classification or prediction tasks (Vincent 2021). As GenAI technologies advance, they increasingly impact knowledge work, requiring continuous adaptation of task performance and decision-making (Alavi et al. 2024). In this context, knowledge workers - such as engineers, scientists, consultants, and information technology specialists - are the focus of this transformation. Their roles are characterized by the ability to interpret, synthesize, and apply complex information in problem-solving scenarios (Davenport 2005). Unlike routine-based professions, knowledge work involves high degrees of autonomy, decision-making under uncertainty, and tasks that require critical thinking, creativity, and expertise-driven judgment (Nonaka and Takeuchi 1995). A key aspect of knowledge work is the reliability and validity of information, which has become a growing concern with the increasing integration of GenAI tools such as ChatGPT, and GitHub Copilot (Dwivedi 2023). While these tools enhance efficiency by expediting research, content generation, coding, and design tasks, they also introduce risks such as misinformation, biases, and hallucinations - limiting their applicability in high-stakes decision-making contexts (Bommasani et al. 2021). The performance of GenAI remains inconsistent across different domains; for instance, while it accelerates software development by automating code generation (Wang et al. 2023), its effectiveness in legal and medical fields is constrained by the necessity for verifiable and legally defensible outputs (Nikolaidis et al. 2023; Rahman and Watanobe 2023). Specific knowledge tasks that are increasingly affected by GenAI integration are, for example, automating literature reviews, generating hypotheses, and conducting preliminary data exploration in the area of scientific research (Sallam 2023), or assisting in debugging, code completion, and architecture suggestions in the area of software development (Yue et al. 2023). Despite the efficiency gains, knowledge workers remain cautious about the trustworthiness of GenAI-generated outputs. Research indicates that while users acknowledge the productivity benefits, their expectations often exceed actual performance, particularly concerning accuracy and ethical AI considerations (Reis et al. 2020). The reliability of GenAI in critical fields depends on the development of rigorous validation frameworks, hybrid human-AI decision models, and regulatory oversight (Dwivedi 2023). As knowledge workers are key adopters and drivers of AI integration, it is essential to assess both the benefits and risks associated with GenAI adoption in knowledge work settings (Ritala et al. 2024). Therefore, it is important to understand both the benefits and the challenges to ensure its effective usage in work routines (Goto 2023).

2.2 Socio-technical systems theory (STS)

STS is a theoretical framework that examines the interdependence between technical and social systems within organizations (see Figure 1). Originally developed in the 1950s by Trist and Bamforth (1951) in the context of work organization, STS emphasizes that technological innovations cannot be viewed in isolation but must always be analyzed in interaction with social structures, processes, and cultural factors in order to achieve the best possible results. For this paper and from our theoretical understanding, we do not separate technology from tasks as originally done by Bostrom and Heinen (1977). We refer to technology as something that is used to complete a task and thus is part of it. We adopt a pragmatic view in which tasks and technologies are inseparably linked in practice, particularly in GenAI contexts, where the system itself actively shapes how tasks are structured and executed (e.g., through content generation or decision support). Each relationship involves entry points for tensions, which we display in Figure 1 and explain in more detail in Section 4.

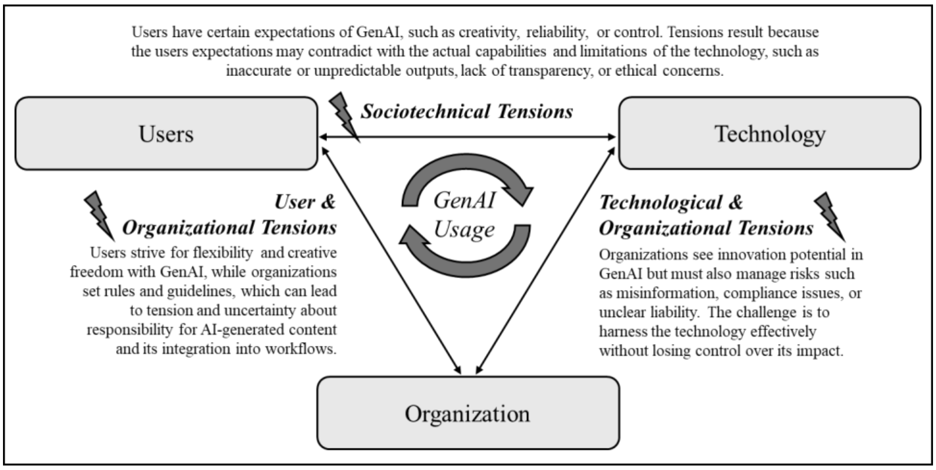

Figure 1. STS in the context of GenAI Usage.

In the context of information systems, STS is often used to understand the impact of digital technologies on organizations and work processes (Baxter and Sommerville

2011). As GenAI emerges, new tensions result as users, organizations, and, in our context, GenAI-driven technologies interact (Lindell and Utterberg Modén 2025). In this context, we decided to draw on STS because it provides a valuable framework for understanding the changing nature of knowledge work and helps us understand how GenAI-driven technologies reshape users, technology usage, and routines in organizations. In addition, STS helps us to explain the tensions that arise in the use of GenAI by recognizing the two-sided impact of technological change. While GenAI can be used to enhance the speed of knowledge-intensive tasks and enable new forms of productivity, it also generates challenges, for example, related to trust, privacy, and ethical considerations (Marimon et al. 2024). Integrating GenAI into knowledge work requires balancing efficiency improvements with potential risks, such as reliance on non-transparent algorithms, data security concerns, and the potential to reinforce biases in automated outputs (Laine et al. 2025). By acknowledging such tension, STS enables a deeper understanding of the socio-technical trade-offs involved in the use of GenAI and highlights the need for organizations to develop implications that align technological advances with user-related values and organizational goals.

3 Research Design

Given the novelty of GenAI research, we applied a sequential mixed-methods approach: a systematic literature review identified initial tensions (Section 3.1), which were then enriched through qualitative interviews (Section 3.2). Grounded in STS (Bostrom & Heinen 1977), we use STS dimensions (social, technical, sociotechnical) to analyze these tensions. This combined approach enables us to locate and typify tensions in GenAI usage.

3.1 Phase 1: Extracting Tensions from the Literature Corpus

First, the existing literature was consulted to obtain a comprehensive theoretical overview of GenAI and the associated areas of tension. The systematic literature review was based on the established guidelines by vom Brocke et al. (2009) and Webster and Watson (2002). In the beginning, the search space was defined by considering scientific publications on GenAI and tensions from familiar databases of information systems (ACM Digital Library, AIS eLibrary, IEEE Xplore, ScienceDirect, Scopus). To ensure the most comprehensive coverage possible, both the abbreviation GenAI and the full-term Generative AI were integrated into the search string. Due to the high number of publications on GenAI, the search was limited to titles, abstracts, and keywords. Figure 1 gives an overview of the systematic literature review, including the used search string.

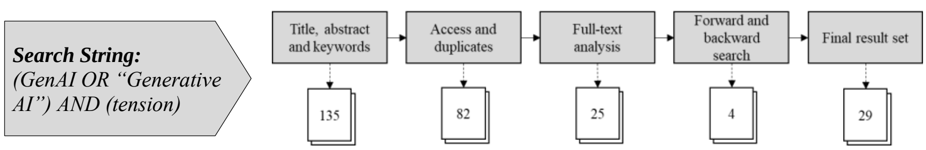

Figure 2. Systematic Literature Review.

The literature search yielded a total of 135 publications. After identifying potentially relevant studies, a multi-stage filtering process was carried out using defined exclusion criteria: First, duplicates, inaccessible, and not yet published studies were removed, which reduced the number of remaining articles to 82. Finally, we included only studies with a clear focus on GenAI in the context of knowledge work. For example, we excluded papers focusing on technologies such as deep learning (e.g., Jia et al. 2024 or Hao et al. 2023) or domain-specific applications such as healthcare (e.g., Delsoz et al. 2023 or Yang et al. 2024) or music (e.g., Larsen and Zhu 2024 or Kanhov et al. 2025). Included studies focused on GenAI use in domains such as education, software development, journalism, and public sector innovation, contexts that exemplify core dimensions of knowledge work. After applying all exclusion criteria, we identified 25 papers as relevant. In addition, a backward search was carried out, which identified four further relevant articles. A total of 29 publications were subjected to an in-depth content analysis. We coded the final literature corpus using STS, assigning each relevant passage to one or more STS dimensions (social, technical, sociotechnical) based on its thematic focus and contextual framing (see Section 2.2 and illustrative examples in Table 1).

Table 1. Examples of the Literature Analysis.

Quote from Literature	Assigned code	STS
"Although these measures provide a degree of protection for GDPR principles, they fall short of fully addressing the challenges posed by the datasets and probabilistic algorithms that ChatGPT uses." (Cordella and Gualdi 2024, p. 10)	Data protection requirements contradict the nature of GenAI	Sociotechnical
"For example, several studies show that users' lack of trust in generative models develops due to the model's lack of contextual understanding (Ali et al. 2023; Miao and Wu 2021; Xylogiannopoulos et al. 2024)." (Obreja et al. 2025, p. 2)	Lack of trust in GenAI due to a lack of contextual understanding	Social

3.2 Phase 2: Collecting and Reaffirming Tensions from an Interview Study

Second, we extended and triangulated the results of the systematic literature review by interviewing knowledge workers who use GenAI. Research can benefit from using interviews to examine a person's or a group's experiences and opinions on a certain subject in greater detail (Gill et al. 2008). Given that GenAI is still a relatively young field, we thought this was a sensible strategy. Our sampling criteria were as follows: (1) The interviewees had to be using GenAI for at least 2 years, (2) work in academia (e.g., a university or non-university research institution), (3) be active as knowledge workers in the field of Information Systems, and (4) work in one country (i.e., Germany) to avoid cultural biases. This ensured that each interviewee had the relevant knowledge to contribute to investigating our shared phenomenon, namely GenAI, in knowledge work. We deliberately chose academia as the prototypical context for knowledge work, as it is characterized by high cognitive demands, autonomy and strict standards for information validity and ethical data use (Davenport 2005; Drucker 1999), conditions under which the use of GenAI is particularly tense. In total, we interviewed 18 informants. We chose a semi-structured approach to enable the interviewees to draw flexibly from their rich experiences (Myers and Newman 2007). Each interview took between

22 and 57 minutes (⌀ 30 minutes), resulting in over 9 hours of transcribed material on the experiences with GenAI in knowledge work. To analyze our interviews, we followed a qualitative content analysis. Two of the authors coded the interview transcripts to identify tensions.

4 Consolidated Findings and Discussion

The implementation of GenAI in knowledge work confronts organizations with a variety of complex and often contradictory challenges and opportunities. Figure 1 displays some entry points for tensions that result from the relationships between users, technology, and organizations. The dual nature of challenges and opportunities is often referred to in the academic literature as “tensions”, a concept that describes the simultaneous existence of conflicting requirements or expectations within a system (Ciriello and Mathiassen 2022; Hietala et al. 2024). Tensions are inherent in complex STS, where technological innovations interact with existing social structures, creating diverging interests and requirements (Jarvenpaa and Lanham 2014). These tensions are particularly relevant in knowledge work, as knowledge work is characterized by a high level of cognitive complexity, self-regulated work processes, and the need for critical reflection (Drucker 1999; Newell et al. 2009). The introduction of GenAI, for example, can lead to a significant increase in productivity by automating time-consuming tasks. However, this technology also raises key ethical issues relating to aspects such as data protection, transparency, and the quality of the content generated (e.g., Cordella and Gualdi 2024; Marimon et al. 2024). or knowledge workers, who frequently engage in tasks requiring creativity, problem-solving, and domain expertise, the impact of GenAI can be both empowering and disruptive (Someh et al. 2025).

Our findings reveal multiple tensions in the use of GenAI in knowledge work (see Table 2), based on a combined analysis of the literature and qualitative interviews (see Section 3). While GenAI provides significant benefits by enhancing productivity and simplifying tasks, it also introduces challenges that must be addressed for sustainable and responsible use.

4.1 The Social View

From our analysis, we extract a tension between **productivity** and **reflection**. GenAI increases efficiency but may lead to *blind reliance* and *reduced critical* reflection on generated content (Henkenjohann and Trenz 2024; Söllner et al. 2024). This can be seen as a form of *“blind trust”* (IP2). This is particularly critical in knowledge work, where professionals are required to engage deeply with information, verify its accuracy, and apply nuanced judgment in decision-making processes (Boulus-Rødje et al. 2024). Several interviewees reported a considerable increase in efficiency because of GenAI. IP9 describes: *“It has definitely made me more productive. I've just seen that when evaluating things. [...] It's a lot faster than when I do it myself.”* IP14 expresses a similar opinion: *“My stack overflow usage has been reduced, I would say by 99 percent because I can find out everything much faster via ChatGPT.”* IP2 also emphasizes the importance of GenAI for their own way of working: *"I wouldn't know how I work without it today. So, if someone took it away from me today, I'd be lost."* However, GenAI's impact on knowledge work goes beyond efficiency gains. Some interviewees point out potential risks, particularly regarding reduced reflection on the content provided. This phenomenon aligns with the risk of cognitive deskilling, where over-reliance on AI weakens critical thinking abilities in complex work settings (Gerlich 2025). IP9 points out: *"You're tempted to simply believe what it says and it's quite a challenge to really question whether it's true."* IP15 describes this as a possible cognitive regression: *"The negative thing is that if you rely too much on GenAI, you've regressed a bit cognitively."* IP7 refers to the tension between increasing productivity and the quality of results: *"I think you work faster, but perhaps the quality is not better."* IP1 even reports cases in which presentation slides are completely created by GenAI in the shortest possible time: *"I know people who now only have their entire slides created by GenAI within five minutes."* **Responses:** To mitigate this, organizations should implement *human-in-the-loop* models, ensuring that AI-generated insights undergo manual validation before implementation (Hietala et al. 2024). Additionally, critical AI literacy training should be incorporated into workplaces to equip users with the skills to evaluate AI-generated content critically (Wang et al. 2023).

Table 2. Tensions and Solution Approaches.

	Tension	Solution Approaches
Social	**Productivity-Reflection tension:** GenAI increases efficiency but may lead to blind reliance and reduced critical reflection on generated content	Implement ***human-in-the-loop models*** to ensure manual validation of AI-generated insights, provide AI compliance training programs to ensure responsible AI usage
Social	**Availability-Reliability contradiction:** GenAI provides 24/7 access to information, but availability does not equate to reliability, increasing the risk of misinformation	Integrate certainty ***scores and fact-checking tools*** into AI-generated content, develop internal guidelines emphasizing human verification of AI-generated information
Technical	**Efficiency-Traceability dilemma:** AI-generated content is produced quickly, but the lack of clear source references makes verification difficult, particularly in scientific and professional settings	Implement AI-generated ***citation mechanisms*** to improve source traceability, utilize explainable AI techniques to clarify AI decision-making processes
Technical	**Usefulness-Transparency tension:** GenAI is perceived as a highly useful tool, yet the lack of transparency in how outputs are generated limits trust in its use	Require AI providers to ***disclose model architectures, training data sources***, and ***biases***, and enable ***user-controlled transparency*** settings to improve explainability
Sociotechnical	**Regulatory-Freedom ambivalence:** GenAI is widely accessible, yet the lack of clear regulations raises ethical and legal concerns regarding its responsible use	Establish ***internal AI ethics and governance policies*** to regulate AI use within organizations, standardize global AI regulations to ensure ethical AI implementation
Sociotechnical	**Convenience-data protection tension:** While GenAI simplifies work processes, concerns about data privacy and the security of sensitive information remain	Develop ***privacy-by-design AI architectures*** to automatically anonymize sensitive data, implement corporate AI policies restricting the input of confidential data into external AI tools

GenAI provides 24/7 access to information, however, this **availability** does not automatically ensure **reliability**. This is *contradictory* since one might assume that constant accessibility leads to improved efficiency. Yet, a lack of reliability of GenAI results increases the risk of misinformation (Ritala et al. 2024). Users often assume that AI-generated content is accurate despite lacking verifiable sources or fact-checking mechanisms (Wagner et al. 2020). Several interviewees point out that GenAI simplifies access to information. IP9 describes this as follows: *"The hurdle is no longer so high, I would say. [...] Then I quickly ask ChatGPT, something will come up."* However, this constant availability can lead to users treating the information they receive uncritically. IP2 comments: *"I think that this critical reflection on the answers is simply not done."* Several interviewees emphasized the need for human control. IP9 points out that despite the quick responses, a basic understanding is still required to correctly evaluate the generated content: *"You have to specify very precisely what you want, and you still need a basic understanding of what you are doing."* IP10 and IP13 also warn of possible errors in the generated answers. IP10 emphasizes: *"It can be error prone. You definitely have to check that."* Similarly, IP13 emphasizes: *"You always have to check the output that you get. So, you can never assume that what the program writes can really be passed on directly."* This is particularly relevant for knowledge workers, who must ensure the accuracy and reliability of the information they use in their decision-making processes. Their work often requires a high level of precision, and errors based on incorrect AI-generated content can have significant consequences (Drucker 1999). **Responses:** To address this, AI providers should integrate certainty scores, fact-checking tools, and external verification systems to indicate the trustworthiness of responses (Ali et al. 2023). Furthermore, organizations should establish clear guidelines on AI use, ensuring that employees do not rely on AI-generated content without independent verification (Obreja et al. 2025).

4.2 The Technical View

AI-generated content is produced rapidly, but the lack of clear source references makes verification difficult, particularly in scientific and professional settings (Rahman and Watanobe 2023). This poses a dilemma between **efficiency** on the one hand and **traceability** on the other. Users often struggle to determine whether AI-generated insights are fact-based or fabricated (Nikolaidis et al. 2023). In knowledge work, where credibility is crucial, professionals require transparent AI outputs that can be audited and cross-verified with reliable sources (Díaz-Rodríguez et al. 2023). Several interviewees emphasize the importance of source information in verifying the generated content. IP9 emphasizes: *"In my specific context, sources would always be very important so that I know where this information comes from."* IP4 adds: *"I mean, a lot of key points come out, but somehow, it's still not that accurate. Even if sources are mentioned, they don't quite fit."* Similarly, IP2 demands: *"AI should work with evidence from the start and provide references under each answer."* Although the speed advantage of GenAI is recognized, it is linked to concerns about the quality of the results. IP7 describes this tension as follows: *"I think you work faster, but maybe the quality is not better."* GenAI is perceived as unreliable, particularly in scientific contexts. IP11 emphasizes: *"But it* *can't be used for actual scientific work and certainly not when it comes to writing something scientific that you want to publish. Because it's far too flawed for that."* A particularly critical point is the output of invented publications or incorrectly assigned authors, as IP11 describes: *"Especially for literature research. Absolutely useless, because fantasy publications that don't even exist are simply given as answers. Or titles and authors are mixed up or something similar. So, it's really useless for that."* The apparent plausibility of the generated content is also critically reflected upon. IP14 points out: *"So it seems like it makes sense, but when you take a closer look, you think, what kind of nonsense is this?"* IP13 expresses similar frustration regarding ChatGPT: *"With ChatGPT, for example [...] it annoys me that you don't get any sources."* **Responses:** To address this, AI models should incorporate citation mechanisms, ensuring that each response includes verifiable references (Obreja et al. 2025). Additionally, Explainable AI techniques should be employed to offer transparency on how AI reaches conclusions (IP17, Laine et al. 2025).

GenAI is perceived as a highly **useful** tool, yet the lack of **transparency** in how outputs are generated limits trust in its use (Marimon et al. 2024). Users often find AI-generated insights helpful yet opaque, making it difficult to assess biases and decision logic (Sampson 2021). Several interviewees emphasize the usefulness of GenAI in their professional or academic context. IP9 emphasizes that AI significantly speeds up the work process: *"It's much faster than if I did it myself."* IP4 even goes one step further and sees the technology as a future standard: *"I think the whole thing will become a kind of standard, so to speak. We will simply work with it as a matter of principle."* Despite these positive effects, the lack of transparency remains a major challenge. IP6 criticizes the lack of context sensitivity of the generated content: *"I find AI often brings up key points but doesn't really understand the context. That doesn't really help me."* This is particularly problematic in academic and scientific fields, where the accuracy and comprehensibility of information is essential. IP7 points out a common problem: *"If you do literature research with it, the AI gives you papers that don't exist."* **Responses:** Addressing this requires AI providers to openly document model architectures, training data sources, and inherent biases (Vincent 2021). Moreover, enabling user-controlled AI transparency settings, where users can adjust the level of explainability, could improve trust and align AI use with professional expectations (Goto 2023).

4.3 The Socio-Technical View

GenAI is largely **freely** accessible, yet the lack of clear **regulations** raises ethical and legal concerns that produce *ambivalence* (Cordella and Gualdi 2024). While some organizations set internal rules for AI use, the absence of global AI governance frameworks increases risks related to data misuse, bias, and ethical violations (Marimon et al. 2024). Several interviewees point out that widespread use is already taking place, but that no clear regulations yet exist. IP7 describes: *"There is no clear regulation, but everyone uses it somehow."* In this context, IP5 expresses concerns about potential misuse: *"But I'm afraid that people will do it after all."* This reflects broader concerns in knowledge-intensive fields where AI-generated outputs may inadvertently violate data security protocols or intellectual property rights (Ananny 2024). The topic of regulation is becoming increasingly relevant in companies, especially when dealing with sensitive data. IP10 describes a company-specific approach to this: *"We have our own in-house AI. The aim of this is to ensure that we do not put internal company data or company-relevant data into an open AI that does not belong to us, such as ChatGPT. And we have rules that we don't put sensitive data anywhere else."* This statement shows that, despite the free availability of AI tools, companies are establishing internal usage guidelines to ensure data protection and security standards. At a societal level, the extent to which state regulation is necessary is being discussed. IP12 formulates a central question in this regard: "*Perhaps we need to ask the question again: Will there be regulations from the state at some point? Will it somehow regulate how AI is to be used? For what purposes?"* A first step towards state control has already been taken in the European Union, as IP10 emphasizes: *"In Europe, we have the Artificial Intelligence Act, which is unique in that it is the first attempt to regulate AI."* **Responses:** To address this, both organizations and policymakers must develop AI regulations that balance innovation with responsible AI governance (EU AI Act, IP10). Additionally, companies should establish internal AI ethics policies, defining acceptable data usage, bias mitigation strategies, and compliance measures to ensure ethical AI adoption.

While GenAI simplifies work processes and increases efficiency, concerns about **data privacy** and the **handling of sensitive** information remain significant (Wagner et al. 2020). Many users rely on AI to streamline their workflows but risk exposing confidential data in the process. This creates a paradox where the convenience of AI-driven automation clashes with the need to protect sensitive information. Several interviewees highlight the risks of uncontrolled AI use, particularly regarding corporate data protection. IP2 expresses a major concern: *"I can imagine that many trade secrets simply go to the AI when people have emails rewritten via GPT."* IP3 emphasizes the relevance of this issue for companies: *"I think data protection is always a huge issue in companies, of course."* The automatic processing of sensitive content carries the risk of confidential information being disclosed without clear transparency regarding storage or further use. Despite these concerns, many users continue to use AI for efficiency gains. As IP14 describes: *"What I also use it for is email. Emails were always something that I found very time-consuming, always finding the right wording and so on. And now it looks like this: I get an email, then I just write in FHGenie what I'd like as an answer, and then it makes it nice for me."* This statement illustrates how AI is used to optimize work, despite potential risks. Some users attempt to mitigate these risks by adopting their own protective measures. IP7 explains: *"I personally don't upload any data. So, let's say I have an email transcribed, then I take the names out."* At an institutional level, efforts are made to regulate AI usage to ensure compliance with data protection policies. IP9 describes an example from a university: *"The university regulates this centrally and you can get in with your university login so that you don't have to pass on your data, so to speak."* Companies also implement strict internal guidelines. As IP10 states, "And we have rules that we don't send sensitive data anywhere else." However, these rules do not always prevent employees from using AI tools. IP14 remarks: *"In other companies, I'm pretty sure they'll just use it, even if they're not allowed to."* This highlights a contradictory dynamic: GenAI enhances efficiency, but its use also introduces new complexities in handling data securely. IP2 describes this paradox: *"It* *makes things much easier and faster, but at the same time it makes work processes more complex because you're asking more and more questions."* **Responses:** To address these risks, AI providers should implement privacy-preserving architectures, such as federated learning and on-device AI processing, ensuring that data is processed locally rather than being transmitted externally (Rahman and Watanobe 2023). Additionally, organizations should establish enterprise-grade AI policies that restrict employees from inputting confidential data into external AI systems, ensuring secure AI adoption (Henkenjohann and Trenz 2024).

5 Contributions and Conclusion

Our **contributions** are threefold: First, we provide a structured STS-informed framework for understanding tensions in GenAI integration within knowledge work. Second, we offer practical solutions to address the identified tensions, such as human-in-the-loop models, governance policies, and AI literacy training. These measures empower knowledge workers to navigate the complexities of GenAI effectively and responsibly. Third, our findings contribute to broader AI governance discussions by emphasizing the need for structured AI adoption frameworks that mitigate risks while maximizing productivity gains. Furthermore, our empirical insights into real-world challenges inform both organizational AI integration strategies and policymaking efforts, highlighting the necessity of clear regulatory frameworks for the ethical and responsible deployment of GenAI in professional environments.

Despite these contributions, our study has **limitations**. The qualitative interview approach, while providing rich insights, limits generalizability across diverse sectors and cultural contexts. Our focus on knowledge workers in Germany may not fully represent global perspectives. Furthermore, our sample consisted exclusively of academic professionals in the field of Information Systems, which also restricts the scope of our findings, as other domains (e.g., consulting) may exhibit different dynamics. Furthermore, the interview participants were predominantly young, which may influence their perspectives and experiences with GenAI, potentially skewing the findings toward a younger demographic's views. **Future research** should explore the long-term impacts of GenAI across various industries and cultures and seek to establish standardized regulations governing its use. Furthermore, more research is required to explore trust dynamics in human-AI collaboration, focusing on how users perceive AI reliability, how trust can be enhanced through transparency and explainability, and how GenAI impacts critical thinking and decision-making processes in knowledge work.

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