Exploring the Role of Generative AI in Knowledge Sharing and Innovation: A Study of Norwegian Organizations

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Abstract: Generative artificial intelligence (GenAI) is increasingly used in knowledge-intensive work, yet empirical evidence remains limited on how it influences organizational knowledge processes and innovation. Although the rapid diffusion of GenAI technologies has attracted significant attention from researchers and practitioners, there is still a limited understanding of how these tools are integrated into everyday knowledge work and how they contribute to the generation and implementation of innovative ideas. This study examines how knowledge workers in Norwegian organizations use GenAI, the factors that encourage or constrain adoption, and the influence of leadership and organizational culture on its effective use. An exploratory qualitative study was conducted through ten semi-structured interviews with knowledge workers from public- and private-sector organizations. Participants represented a variety of professional roles and organizational contexts, providing insights into both individual and organizational experiences with GenAI. The interview data were analyzed thematically to identify recurring patterns related to knowledge activities, innovation processes, and organizational conditions. The findings show that GenAI supports innovation by facilitating knowledge discovery, synthesis, translation, recombination, idea generation, and concept development. Participants associated its use with faster access to information, accelerated learning, improved problem-solving, and broader exploration of alternatives. Many described GenAI as a valuable cognitive support tool that enhanced creativity and enabled more efficient knowledge sharing across teams. However, they also raised concerns about inaccurate outputs, weak source traceability, privacy, cybersecurity, and excessive reliance on AI-generated content. Additional concerns related to the potential erosion of critical thinking skills and professional expertise if human judgment is not actively maintained. Trust, employee autonomy, and supportive leadership encouraged experimentation, while GDPR compliance, transparency, and professional accountability shaped responsible use. The study conceptualizes GenAI as a conditional knowledge-integration mechanism whose contribution to innovation depends on human validation, organizational learning, and responsible governance. The findings contribute to knowledge management and innovation research by highlighting the organizational capabilities required to harness GenAI while mitigating associated risks.

Keywords: Generative AI, Knowledge management, Organizational culture, Leadership, Innovation, Knowledge workers

1. Introduction

Generative artificial intelligence (GenAI) refers to AI systems capable of generating text, code, images, and other structured content from large training datasets. Organizations increasingly use these systems to support productivity, decision-making, creativity, and innovation (Kaczorowska-Spychalska, Kotula, Mazurek, & Łukasz, 2024; K. Kirchner, Bolisani, Kassaneh, Scarso, & Nima, 2026). Experimental evidence suggests that GenAI can significantly enhance performance in knowledge-intensive tasks. In a randomized controlled trial involving 444 college-educated professionals, (Noy & Zhang, 2023) found that access to ChatGPT reduced task completion time by 40% while improving output quality by 18%. Unlike earlier forms of automation that primarily replaced routine tasks, GenAI can assist professionals with the cognitive, creative, and communicative activities at the core of knowledge work (M. Alavi, Leidner, & Mousavi, 2024). Despite its growing adoption, the knowledge management perspective on GenAI remains fragmented. Existing studies have largely focused on technological capabilities, individual productivity, and creative assistance, while less attention has been devoted to how GenAI influences the organizational knowledge processes that underpin innovation (Roberto, Giuseppe, & Renato, 2026; Storey, 2025). Recent research therefore calls for more systematic examination of the relationship between GenAI, knowledge management, and organizational performance, including both its opportunities and associated risks (M. Alavi et al., 2024; Noy & Zhang, 2023; Sumbal, Amber, Tariq, Raziq, & Tsui, 2024; Tor, 2026).

From a knowledge management perspective, GenAI can be understood as a knowledge-integration mechanism that supports knowledge creation, retrieval, sharing, integration, and application (Qichao et al., 2025). Unlike conventional information systems that mainly store and retrieve information, GenAI can synthesize material from multiple sources, translate knowledge across domains, identify connections between ideas, and support sensemaking in uncertain situations. These capabilities may influence not only individual performance but also the collective knowledge processes through which organizations develop and implement innovation.

Innovation depends on more than access to information. Organizations must also be able to create, share, integrate, and apply knowledge across teams and professional boundaries (Davenport, 1998; Ikujiro Nonaka & Takeuchi, 1995; Yayilgan et al., 2015). Emerging research suggests that GenAI may improve access to dispersed knowledge, support communication across communities of practice, and enable the recombination of knowledge in ways that contribute to innovation. However, its use also creates challenges related to trust, quality assurance, bias, overreliance, and the validation of AI-generated outputs (B. Wiesenfeld & K., 2025; Ritala, Ruokonen, & Ramaul, 2023). Although conceptual research has developed rapidly, empirical evidence remains limited regarding how knowledge workers use GenAI in everyday work and how these practices contribute to innovation. Existing qualitative studies indicate that GenAI can support learning, problem-solving, knowledge creation, and knowledge sharing, but the findings remain fragmented and are often limited to particular industries or occupations (B. Wiesenfeld & K., 2025). Organizational context is another underexplored dimension. Knowledge creation and sharing are influenced by leadership, trust, openness, psychological safety, and organizational culture(Davenport, 1998; Edmondson, 1999; Hansen, Jensen, & Nguyen, 2020; Senge & Sterman, 1992). These factors may determine whether GenAI remains an individual productivity tool or becomes a collective capability that supports innovation (Kathrin Kirchner, Bolisani, Kassaneh, Scarso, & Taraghi, 2025; K. Kirchner et al., 2026; Mariani & Dwivedi, 2024).

This study examines how knowledge workers in Norwegian organizations use GenAI in innovation-related activities. Norway provides a relevant setting because Norwegian working life is commonly associated with high trust, employee autonomy, collaborative decision-making, relatively flat hierarchies, and digital maturity. These characteristics may support experimentation and knowledge sharing. At the same time, strong expectations concerning privacy, transparency, data protection, and professional responsibility may constrain the use of organizational knowledge in GenAI systems.

The study addresses the following research questions:

RQ1: *How do knowledge workers use GenAI to support knowledge processes that contribute to innovation?*

RQ2: *What drivers and barriers do knowledge workers identify when adopting GenAI for creative and analytical innovation tasks?*

RQ3: *How do leadership practices and organizational culture shape employee engagement with GenAI in knowledge-intensive Norwegian organizations?*

By combining knowledge management and innovation research with qualitative evidence from Norwegian knowledge workers, the study contributes empirical insight into how GenAI supports knowledge creation, sharing, integration, and application. It also identifies the organizational conditions that enable or constrain its contribution to innovation. Section 2 presents the theoretical background, Section 3 describes the methodology, Section 4 reports the findings, Section 5 discusses the results, and Section 6 presents the conclusions.

2. Theoretical Background and Literature Review

2.1 Generative AI and the Knowledge-lifecycle

Generative artificial intelligence (GenAI) has emerged as a transformative technology with the potential to reshape how knowledge is created, shared, and applied within organizations. Unlike earlier AI systems focused primarily on automation, prediction, or classification, GenAI can generate content, summarize information, answer complex questions, and support problem solving (Feuerriegel, Hartmann, Janiesch, & Zschech, 2024). As a result, organizations are increasingly experimenting with large language models to support knowledge-intensive work, organizational learning, and innovation (Dell'Acqua, 2025; Feuerriegel et al., 2024).

GenAI research in knowledge management remains fragmented, with greater attention to technology and productivity than to organizational knowledge processes (Roberto et al., 2026; Storey, 2025). Existing studies have focused largely on technological capabilities and productivity outcomes, while less attention has been paid to how GenAI influences organizational knowledge processes.

Knowledge management creates organizational value and innovation through interconnected processes of knowledge creation, capture, sharing, storage, and application (Maryam Alavi & Leidner, 2001; Becerra-Fernandez, Sabherwal, & Kumi, 2024; Wiig, 1993).

GenAI can support multiple knowledge-lifecycle stages by enhancing knowledge creation, retrieval, sharing, synthesis, and decision-making (M. Alavi et al., 2024; Jukka Luoma, 2025; Zhang, 2026).

GenAI influences organizational learning by changing how knowledge is searched, created, retained, and transferred. Its strongest contributions appear in knowledge discovery, retrieval, documentation, and explicit knowledge synthesis, while knowledge sharing and application remain more dependent on organizational context and work practices (Kathrin Kirchner et al., 2025; Wiesenfeld & Katherine, 2025) (Wiesenfeld & K., 2025; Kirchner et al., 2025). It may also support innovation through external knowledge search, knowledge absorption, and the integration of diverse expertise (Chi, Hao, & Mengya, 2026; K. Kirchner et al., 2026)

From a SECI perspective, GenAI supports externalization and combination by helping users articulate tacit insights and recombine knowledge across domains (B. Wiesenfeld & K., 2025; Ikujiro Nonaka & Konno, 1998; Ikujiro Nonaka & Takeuchi, 1995). These capabilities are particularly relevant for innovation, which often depends on the integration and recombination of dispersed knowledge activities (K. Kirchner et al., 2026; Li, Ring, Jin, & Bajaba, 2025). However, the concept of *ba* highlights that knowledge creation also depends on organizational conditions such as trust, collaboration, and psychological safety (Ikujiro Nonaka & Konno, 1998).

2.2 Drivers and Barriers to the Adoption of GenAI for Innovation Processes

GenAI adoption in innovation work is shaped by technological, cognitive, professional, and organizational factors.

The Technology Acceptance Model (TAM) identifies perceived usefulness and perceived ease of use as key determinants of technology adoption (Davis, 1987). Applied to GenAI, perceived usefulness relates to the extent to which knowledge workers believe AI tools enhance their ability to perform innovation-related activities. Experimental evidence suggests that GenAI can improve output quality while reducing the time required to complete knowledge-intensive tasks (Noy & Zhang, 2023). Beyond productivity gains, GenAI has been associated with accelerated ideation, cross-domain knowledge synthesis, and reduced knowledge search costs, all of which may support innovation by enabling knowledge workers to explore broader solution spaces and combine knowledge from multiple sources (Mariani & Dwivedi, 2024).

From a knowledge management perspective, these capabilities are particularly important because innovation depends on the discovery, integration, and application of dispersed knowledge. GenAI can facilitate knowledge recombination, support exploratory learning, and accelerate the acquisition of new knowledge, thereby contributing to innovation activities (Calvino, Reijerink, & Samek, 2025).

However, adoption cannot be explained by perceived benefits alone. While many knowledge workers view GenAI as a tool that enhances problem solving, creativity, and learning, others express concerns regarding the future value of their expertise and professional contribution. Such concerns have been described as professional identity anxiety, reflecting fears that reliance on AI-generated outputs may weaken perceptions of competence and expertise (M. Alavi et al., 2024). Trust and knowledge quality represent additional challenges. Although GenAI can generate coherent and persuasive outputs, users often face difficulties assessing their accuracy and reliability. The effort required to validate AI-generated content may offset some of the productivity gains associated with its use(K. Kirchner et al., 2026). From a knowledge management perspective, this challenge reflects the importance of trust in effective knowledge exchange (Davenport, 1998). Excessive reliance on GenAI may weaken critical thinking, reflection, and expertise development, which remain essential for innovation. Ethical, privacy, cybersecurity, and bias concerns may limit GenAI adoption, especially where sensitive information is involved. Unclear governance and accountability can also discourage experimentation, reflecting the broader influence of organizational policies on knowledge-sharing behaviour (Kathrin Kirchner et al., 2025; Senge & Sterman, 1992; Sumbal et al., 2024) .

2.3 Leadership and Organizational Culture as Enablers of AI-supported Knowledge Sharing and Innovation

The contribution of GenAI to innovation depends not only on technological capabilities but also on the organizational environment in which it is adopted and used. Knowledge management research has long emphasized that knowledge creation, sharing, and application are shaped by leadership, organizational culture, and learning environments. As GenAI becomes increasingly embedded in knowledge-intensive work, these factors are likely to influence whether AI-generated knowledge remains an individual productivity aid or develops into a collective capability that supports innovation.

Leadership plays an important role in shaping employee engagement with new technologies. Transformational leadership, characterized by intellectual stimulation, support for learning, and encouragement of experimentation, has consistently been associated with higher levels of creativity, knowledge sharing, and innovation. In contrast, transactional leadership emphasizes compliance and performance control (Dionne, Yammarino, Atwater, & Spangler, 2004). In the context of GenAI, transformational leaders may be more likely to encourage experimentation, knowledge sharing, and collective learning around AI-supported practices.

The rapid emergence of GenAI has also raised questions regarding reliability, accountability, privacy, and ethical use. In such contexts, leaders can support responsible experimentation by providing guidance, clarifying expectations, and fostering learning opportunities.

Recent studies further suggest that organizations derive greater value from GenAI when they establish support structures such as communities of practice, expert networks, and mechanisms for sharing and validating AI-generated knowledge (M. Alavi et al., 2024; B. Wiesenfeld & K., 2025).

Psychological safety is another important condition for AI-supported innovation. Employees are more likely to experiment with GenAI, discuss limitations, and share lessons learned when they feel comfortable taking interpersonal risks and expressing uncertainty(Edmondson, 1999). Similarly, organizational culture influences how employees engage with GenAI. Organizations may promote innovation through formal policies while maintaining norms that discourage experimentation, risk-taking, or knowledge sharing. Such inconsistencies can limit the contribution of GenAI to organizational learning and innovation (Schein, 2010).

The importance of trust, openness, and collaboration has long been recognized within the knowledge management literature (Davenport, 1998; Koenig, 2011). These factors are particularly relevant in the context of GenAI, where employees often need to share prompts, discuss AI-generated outputs, and collectively assess the quality and relevance of AI-supported insights. Recent research suggests that GenAI can accelerate idea generation, facilitate cross-domain knowledge synthesis, and reduce knowledge search costs, but these benefits are more likely to emerge in environments that support learning and experimentation (Mariani & Dwivedi, 2024; Storey, 2025; Tor, 2026). These organizational factors are particularly relevant in the Norwegian context, where trust, employee autonomy, collaborative decision-making, and relatively flat hierarchies are often regarded as important characteristics of organizational life. Such conditions may encourage experimentation and collective learning while also reinforcing expectations regarding transparency, accountability, and responsible innovation (Lasse & Bram, 2026). Leadership and organizational culture influence whether GenAI supports innovation, but empirical evidence on their role remains limited. This leads to RQ3: How do leadership practices and organizational culture shape employee engagement with GenAI in knowledge-intensive Norwegian organizations?

3. Methodology

This study adopts an exploratory qualitative design to examine how knowledge workers in Norwegian organizations use GenAI to support knowledge sharing and innovation. The aim was not to measure the extent of adoption, but to understand how participants experience and apply GenAI in innovation-related knowledge work.

The empirical material consists of ten semi-structured interviews with informants referred to as P1–P10. Participants were recruited through purposive sampling because they had direct professional experience with GenAI. They are considered knowledge workers because their roles involve creating, interpreting, applying, and sharing specialized knowledge in areas such as research, software development, consulting, management, advisory work, analysis, and innovation.

The diversity of participants was intentional. The study does not compare sectors statistically, but explores how GenAI is used across different knowledge-intensive contexts. The informants are comparable because all used GenAI in tasks involving knowledge processing, problem solving, decision support, or innovation-related work.

The face-to-face interviews lasted between 30 and 60 minutes and focused on three themes: GenAI use in knowledge and innovation processes, drivers and barriers to adoption, and the influence of leadership, organizational culture, and the Norwegian work context. Notes were taken during and immediately after each interview, and the material was analysed thematically to identify recurring patterns.

As the study is based on a limited and heterogeneous sample, the findings are not statistically generalizable. Instead, they provide analytical insights and a basis for future large-scale investigation.

Table 1: Interview participant profile

Participant	Organization type	Role category	GenAI use	Interview focus
P1	Public sector	Senior advisor/manager	Frequent	Decision support, document drafting, governance
P2	Higher education/research	Researcher /professor	Daily	Research ideas, teaching material, proposal development
P3	Consulting/services	Consultant	Frequent	Client analysis, knowledge synthesis, workshops
P4	Technology/software	Software developer/engineer	Daily	Coding support, problem framing, technical documentation
P5	Engineering/industry	Project manager	Frequent	Planning, risk identification, reporting
P6	Public/regulated organization	Knowledge specialist/advisor	Occasional	Privacy, GDPR, responsible use
P7	Energy/technology	Innovation manager	Daily	Idea generation, opportunity scanning, concept development
P8	Public administration	Advisor	Frequent	Summarization, policy interpretation, validation
P9	Finance/business services	Business analyst/manager	Daily	Scenario analysis, decision support, strategy
P10	SME/entrepreneurship	Manager/entrepreneur	Daily	Business development, market analysis, experimentation

4. Findings and Discussion

The thematic analysis identified three main categories corresponding to the research questions. The first category concerns GenAI-supported knowledge processes, including knowledge discovery, synthesis, translation, and recombination. The second category concerns adoption drivers and barriers, including productivity, learning, creativity, reliability, privacy, cybersecurity, and overreliance. The third category concerns organizational conditions, including leadership support, trust, autonomy, psychological safety, and responsible governance.

Within these categories, several subcategories emerged. Participants working with research and innovation described using GenAI to organize dispersed information and transform early ideas into project concepts and funding proposals (P2, P7). Participants in public and regulated organizations emphasized confidentiality, GDPR compliance, source validation, and the need to avoid entering sensitive organizational data into public AI tools (P6, P8). Technology- and entrepreneurship-oriented participants emphasized rapid experimentation and the ability to compare alternative solutions before committing resources (P4, P7, P10). These patterns show that GenAI use was shaped both by the nature of knowledge work and by the organizational context in which it was applied.

Table 2: GenAI Contributions, Opportunities, Challenges and Organizational Conditions for Innovation in Norwegian Organizations

Innovation activity / KM process	Reported use of GenAI	Opportunities	Challenges	Organizational conditions
Knowledge discovery and problem framing	Searching, summarizing and synthesizing reports, regulations, funding calls and other internal or external sources.	Faster access to dispersed knowledge; earlier opportunity identification; improved understanding of complex issues.	Incomplete or outdated information; superficial analysis; loss of contextual nuance.	AI literacy, trusted sources, domain expertise and critical evaluation.

Innovation activity / KM process	Reported use of GenAI	Opportunities	Challenges	Organizational conditions
Idea generation and creativity support	Brainstorming, scenario development and generation of alternative solutions.	Accelerated ideation; broader solution spaces; support for employee-driven innovation.	Generic or repetitive suggestions; limited originality; possible convergence around similar ideas.	Psychological safety, autonomy and willingness to experiment.
Knowledge synthesis and recombination	Combining technical, regulatory, sustainability, business and user-related knowledge across domains.	Cross-disciplinary learning; improved communication across professional silos; innovation through knowledge recombination.	Weak traceability; difficulty assessing novelty; risk of oversimplifying specialist knowledge.	Knowledge-sharing culture, collaboration and access to diverse expertise.
Concept development and analytical support	Drafting project concepts, business cases, funding proposals, roadmaps and comparisons of alternatives.	Faster concept development; improved decision preparation; more structured innovation proposals.	Hallucinations, factual inaccuracies, bias and false confidence in apparently coherent outputs.	Leadership support, human oversight and systematic validation practices.
Knowledge sharing and organizational learning	Preparing summaries, translations, reports, training material and lessons-learned documentation.	Faster diffusion of knowledge; improved accessibility of expertise; reusable organizational learning.	Reduced critical reflection; overreliance on AI-generated summaries; loss of tacit or contextual knowledge.	Trust, openness, communities of practice and collaborative learning.
Learning, competence and expertise	Exploring unfamiliar topics, acquiring background knowledge and testing alternative explanations or approaches.	Accelerated learning; lower threshold for participating in innovation-related discussions.	Potential deskilling; reduced cognitive effort; steep learning curve for effective prompting and validation.	Continuous-learning culture, AI competence and responsible use.
Responsible innovation and employee engagement	Using GenAI in daily knowledge-intensive work while considering privacy, governance and professional responsibility.	Greater efficiency, experimentation and broader participation in innovation activities.	Privacy, GDPR, cybersecurity, confidentiality, accountability, gender bias and professional identity concerns.	Clear governance, transparency, employee involvement, supportive leadership, high trust and autonomy.

RQ1: GenAI as a Knowledge-Integration Mechanism for Innovation

The findings show that GenAI functions as a knowledge-integration mechanism rather than simply as a productivity tool. Across the participant groups, it was used to access, synthesize, translate, and recombine knowledge from different sources. In doing so, GenAI helped participants connect fragmented information and make it more usable in innovation activities. This finding is consistent with previous research suggesting that GenAI supports knowledge creation, retrieval, sharing, and application by augmenting cognitive capabilities and facilitating knowledge integration (Alavi et al., 2024; Zhang, 2026).

GenAI appeared to be particularly valuable during the early stages of innovation, including opportunity identification, problem framing, idea generation, and concept development. Rather than generating innovation independently, it helped participants explore alternative perspectives, combine existing knowledge in new ways, and develop initial ideas more quickly. This supports the view that innovation often emerges through the recombination and reconfiguration of existing knowledge rather than solely through entirely new discoveries (Nonaka & Takeuchi, 1995).

This role was particularly visible among participants involved in research and innovation activities. Participants from higher education and innovation management described using GenAI to organize dispersed information, develop alternative formulations, and transform initial ideas into more structured project concepts and preliminary funding proposals. For example, P2 and P7 used GenAI to prepare early versions of project descriptions that were subsequently reviewed, contextualized, and refined through human judgement. This illustrates how GenAI can support the transition from fragmented knowledge and loosely formulated ideas to more coherent innovation concepts.

The findings also support recent research suggesting that GenAI is especially effective in activities involving the synthesis and transformation of explicit knowledge (Cerchione et al., 2026; Kirchner et al., 2025). However, participants consistently emphasized that AI-generated outputs required validation and contextual interpretation. GenAI accelerated access to and integration of knowledge, but it did not replace domain expertise, professional judgement, or collective sensemaking.

Overall, the findings suggest that GenAI contributes to innovation by helping knowledge workers identify, connect, restructure, and apply knowledge more efficiently. Its value does not lie in autonomously producing reliable knowledge, but in supporting employees as they interpret and recombine knowledge within a specific organizational context. GenAI can therefore be understood as a conditional knowledge-integration mechanism whose effectiveness depends on human validation, contextual expertise, and the organizational practices through which its outputs are evaluated and applied.

RQ2: Drivers and Barriers to GenAI Adoption for Innovation

Participants adopted GenAI because it provided faster access to information, supported brainstorming, accelerated learning, and improved productivity. These benefits were particularly valuable during early innovation activities requiring rapid exploration of unfamiliar topics and alternative solutions (Noy & Zhang, 2023; Mariani & Dwivedi, 2024).

Adoption was constrained by concerns about reliability, source traceability, privacy, cybersecurity, and overreliance. Participants noted that convincing outputs could still be inaccurate or fabricated, making verification essential. They also expressed concern that excessive automation of analytical work could weaken critical thinking and professional expertise, reflecting wider concerns about trust, professional identity, and human validation (Alavi et al., 2024; Kirchner et al., 2025).

These concerns were especially evident in public and regulated organizations. Participants P6 and P8 avoided entering sensitive information into publicly available tools and emphasized confidentiality, GDPR compliance, and validation against trusted sources. GenAI adoption therefore depends on combining efficiency gains with data protection, critical evaluation, and continued investment in professional judgement.

RQ3: Leadership, Organizational Culture, and the Norwegian Context

Leadership and organizational culture strongly influenced employee engagement with GenAI. Trust, autonomy, openness, and psychological safety encouraged employees to experiment, exchange experiences, and learn collectively, supporting established knowledge management research on organizational learning and innovation (Davenport & Prusak, 1998; Edmondson, 1999).

Participants valued leaders who enabled experimentation, encouraged knowledge sharing, and provided guidance rather than relying primarily on control. Technology- and entrepreneurship-oriented participants emphasized rapid testing and comparison of alternatives before committing resources. In these settings, employee autonomy and supportive leadership enabled GenAI to be used iteratively for idea testing, scenario exploration, and solution development (P4, P7, P10). The Norwegian context appears to create a specific balance between experimentation and responsibility. Trust, autonomy, collaborative decision-making, and relatively flat hierarchies encouraged employees to test GenAI and share emerging practices. However, strong expectations concerning transparency, GDPR compliance, professional responsibility, and data protection also limited how organizational knowledge could be used in GenAI systems. This suggests that the Norwegian case is not only characterized by openness to experimentation, but also by a strong concern for responsible and accountable use. Leadership is therefore important not simply for encouraging adoption, but for creating boundaries that allow employees to experiment safely.

5. Conclusion

This study shows that GenAI supports knowledge sharing and innovation in Norwegian organizations by facilitating knowledge discovery, synthesis, translation, recombination, idea generation, and concept development. Its adoption is encouraged by productivity gains, accelerated learning, and broader access to knowledge, but constrained by concerns regarding reliability, privacy, deskilling risks, cybersecurity, bias, and overreliance.

Trust, employee autonomy, collaborative practices, and supportive leadership encouraged experimentation, while expectations concerning transparency, accountability, and GDPR compliance reinforced the need for responsible governance. GenAI should therefore be understood as a knowledge-integration mechanism whose contribution to innovation depends on human judgement, organizational culture, and responsible use.

As the study is exploratory and based on a limited number of interviews, the findings are not statistically generalizable. Future work will use a large-scale survey of knowledge workers in Norwegian organizations to examine these relationships further.

Ethics Declaration: Formal ethical approval was not required for this exploratory study under the applicable institutional procedures. Participation was voluntary, and all participants were informed about the purpose of the study and how the interview material would be used. No sensitive personal data were collected, and participants were anonymized and identified only as P1–P10. The interview material was handled confidentially and used exclusively for research purposes.

AI Declaration: A generative AI was used to help improve the language, clarity, and structure of the paper. It was also used to shorten some sections. The tool was not used to collect or analyse the interview data, and it did not generate the findings. All suggestions were reviewed and revised by the authors, who take full responsibility for the final content of the paper.

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