INTEGRATING AI INTO SMALL FIRM KNOWLEDGE WORK: A QUALITATIVE CASE STUDY

DOI
https://doi.org/10.18690/um.fov.4.2026.37

ISBN
978-961-299-152-4

TANJA KORHONEN, HELI KEMPPAINEN
Kajaani University of Applied Sciences, Master School, Kajaani, Finland
tanja.korhonen@kamk.fi, heliekemppainen@gmail.com

The study investigates how artificial intelligence can be integrated into the knowledge work of a micro-enterprise to improve productivity, efficiency and work well-being. A longitudinal single-case design, supported by a master's thesis and follow-up interview, is used to examine how lightweight readiness practices, human-AI task division and iterative workflow adjustments shape adoption under resource constraints. The experimental part was conducted qualitatively within a single firm. The findings indicate that AI can reduce the time spent on preparatory tasks and, in doing so, ease deadline pressure. At the same time, expert oversight is maintained through explicit checkpoints, which appear to help mitigate risks related to automation bias. In this case, the analysis sheds light on AI readiness at a micro level, particularly in how work moves along the assistive-to-advisory spectrum in human-AI collaboration and toward more AI-supported workflows. It also offers practical guidance for small knowledge work firms that are looking for realistic and responsible ways to begin using AI.

Keywords:
AI-integration,
micro-enterprise,
knowledge work,
organisational readiness,
human-AI collaboration

University of Maribor Press

1 Introduction

Artificial intelligence (AI) is spreading quickly in knowledge-intensive work. It offers clear potential to improve productivity and efficiency, but it also raises questions about its effects on employees and whether organisations are ready to adopt it. For micro and small companies, the potential is significant, but so are the challenges. These firms often work with limited resources, fragmented data and a limited capacity for change.

Prior literature (Iansiti & Lakhani, 2020; Colson, 2019) describes AI as a general-purpose technology that can reshape how organisations operate, learn and make decisions. At the same time, it stresses that benefits do not come from technology alone. They depend on having the right capabilities and on integrating AI carefully into everyday work. In this article, AI mainly refers to generative AI.

We examine the research question (RQ): *How can Artificial Intelligence be effectively integrated into the knowledge work of a micro-enterprise to improve productivity and work well-being?* Knowledge work is understood here as the acquisition, creation, combination or application of knowledge (Davenport et al., 1996). The question is timely and responds to a clear gap in the literature. Most existing research focuses on large organisations (Enholm et al., 2022; Jöhnk et al., 2021), while small and medium-sized enterprises (SMEs, see European Commission, 2003) face different challenges. These include lower levels of AI readiness, which can put them at a disadvantage (Yang et al., 2024). At the same time, SMEs form a large part of many economies and account for a significant share of knowledge-intensive work, which makes their AI adoption both economically and socially important.

Generative AI has recently made advanced AI tools easier to access through simple interfaces and cloud services. This makes the RQ especially relevant for small firms, as these changes can lower the barriers to adoption (Brynjolfsson et al., 2023; Longueville et al., 2025). However, there is still limited empirical research on how small firms can use these tools effectively. Most studies focus on large organisations or specific technical solutions rather than broader ways of integrating AI into everyday work (Russo, 2024; Weinberg, 2025).

Including work well-being alongside productivity and efficiency responds to a growing concern in the literature. While AI can improve performance, it may also increase stress, mental workload or job insecurity if it is not introduced carefully (Neumann et al., 2022; Radhakrishnan et al., 2022).

AI often improves productivity by reducing routine tasks and making work more efficient, although most evidence comes from large organisations (Soulami et al., 2024). In these settings, structured implementation and greater resources tend to strengthen the gains (Brynjolfsson et al., 2023; OECD, 2023). In SMEs, AI can also improve performance and efficiency, but the results depend more on factors such as skills, training and organisational support. At the same time, limited resources and other adoption barriers still play a significant role (Sánchez et al., 2025; Wahab & Radmehr, 2024; Fan et al., 2025; Soomro et al., 2024).

Research on micro-enterprises is still scarce. Existing studies focus mainly on conditions for adoption rather than outcomes, suggesting that AI use is shaped by entrepreneurial orientation and technological readiness. Evidence on productivity and well-being effects remains limited and mostly indirect (Nevi et al., 2025), which reflects a broader gap noted in earlier reviews (Soulami et al., 2024; OECD, 2023).

This RQ bridges theory and practice by examining not just whether AI creates value, but *how* it can be integrated in resource-constrained contexts. Existing frameworks for AI readiness and business value (Enholm et al., 2022; Jöhnk et al., 2021) have been developed primarily from large-firm perspectives and require adaptation to small-firm realities. Through this longitudinal case study, we provide empirical insights into how small firms can structure practices and workflows to gain AI benefits while preserving human-centred work.

The study is based on two empirical sources from the same micro-enterprise in professional services. First, we draw on a master's thesis from 2025 that examined AI adoption in a micro-sized firm (Kemppainen, 2025). This was followed by a semi-structured interview with the same firm in 2026, which focused on outcomes, challenges and effects on well-being one year after the initial recommendations. These materials are considered alongside existing research on the business value of AI, organisational and AI readiness, human-AI collaboration in knowledge work, and the workforce effects of machine learning (ML).

This article first reviews prior research on AI value creation, readiness, human-AI task allocation, decision processes, and small-firm AI adoption challenges. It then outlines the research design, presents results integrating empirical insights with theory into a practical model for resource-constrained knowledge work, and concludes with implications, limitations, and future research directions.

2 Previous research

Research on AI in business has shifted from focusing mainly on technology to looking at how organisational capabilities and practices shape outcomes. Studies have examined what supports or hinders AI adoption, as well as its direct effects, such as better decisions and more efficient processes, and broader impacts on performance and sustainability. They also show that many organisations struggle to create value because of skill gaps, resistance to change and unclear goals (Enholm et al., 2022). Research also distinguishes between automation, where tasks are replaced, and augmentation, where AI supports human work. It shows that value depends not only on the technology but also on factors such as management support, strategy and organisational culture (Radhakrishnan et al., 2022).

In SMEs, studies often combine the Technology-Organisation-Environment (TOE) framework, with Diffusion of Innovations (DOI) theory, which explains how new ideas and technologies spread over time. Using these perspectives, research identifies common barriers such as limited data access, lack of skills, cultural resistance and weak governance, and suggests step-by-step ways to support adoption (Sánchez et al., 2025).

Employees may worry about deskilling or job loss when new AI tools are introduced. This highlights the need for clear change management and for presenting AI as a support rather than a threat (Mohd Rasdi & Umar Baki, 2025).

Readiness is often used to explain how organisations adopt digital technologies and AI. Earlier research describes it as a set of capabilities and shows that missing these capabilities is a common reason why initiatives fail. Because of this, readiness should be assessed before moving to wider use (Lokuge et al., 2019).

More recent AI-focused studies identify practical factors that matter, such as data quality, model transparency, skills and governance. These extend the traditional TOE view to better fit AI contexts (Jöhnk et al., 2021; Pumplun et al., 2019). A common finding is that readiness and adoption develop together over time and strengthen each other (Jöhnk et al., 2021).

For SMEs, readiness challenges are often more pronounced. Research shows that smaller firms tend to have lower levels of AI readiness, which can make it harder for them to deal with adoption challenges than for larger organisations (Yang et al., 2024). At the same time, recent studies suggest that agile firms can build practical readiness through lighter approaches, such as cloud-based SaaS tools, flexible structures and small-scale pilots that are developed over time (Oluwamola et al., 2025).

Evidence from a boutique branding consultancy also shows that generative AI can support everyday work by speeding up content creation, reducing managerial workload and gradually strengthening the organisation's knowledge base (Yurong, 2024). These findings offer a useful example for other SMEs. Overall, this supports the idea that creating value from AI often requires changes to the business model as well (Åström et al., 2022).

Human-AI symbiosis research shows that AI supports human cognition in complex, data-rich tasks, while humans provide contextual, intuitive, and ethical judgment under uncertainty. The dominant view is one of intelligence augmentation rather than substitution (Jarrahi, 2018). Decision-making studies similarly advocate a shift from "data-driven" workflows, where humans perform most processing, to "AI-driven" workflows in which machines handle data-intensive analysis and generate options, and humans focus on deliberation guided by values, strategy, and context (Colson, 2019; Iansiti & Lakhani, 2020).

In terms of the workforce, machine learning is often seen as a general technology that changes work rather than simply replacing it. Jobs consist of many different tasks, and not all of them are suitable for automation. As a result, work is changing and expanding rather than disappearing, although the effects are uneven (Brynjolfsson & Mitchell, 2017). From a management perspective, AI is often built on earlier data and analytics capabilities. Organisations can move forward more easily if they build on these existing strengths, if skills, governance and data practices develop at the same time (Davenport, 2018).

Small companies can unlock value from AI if they adopt a deliberate approach to its adoption, ensuring that the foundations for its use are in place. They should also design human-AI task allocations that protect well-being and embed AI into decision workflows with clear guidelines for accuracy, transparency, and responsibility (Horvat et al., 2023; Uren et al., 2023; Cheong, 2024).

3 Methodology

This study brings together two empirical sources from the same micro-sized professional services company and combines them with a focused review of the literature. One source is a master's thesis that examines AI use in a knowledge work firm with fewer than ten employees using an action research approach (Kemppainen, 2025). The article itself is based on a single case study, which is suitable for exploring how and why things happen in real organisational settings where events cannot be controlled (Yin, 2019). The case also makes it possible to follow AI use over time in a micro-enterprise and to capture changes and emerging practices.

The semi-structured interview was conducted in February 2026 with the firm's owner-manager to understand how the earlier recommendations had been implemented. The discussion covered areas such as task types, tools in use, changes in workflows, perceived productivity, error patterns, governance and effects on well-being. The interview lasted 53 minutes and was transcribed immediately afterwards.

The analysis followed an abductive approach, moving between the data and existing theory. In practice, this meant combining inductive observations with theoretical interpretation and revisiting both as the analysis progressed (Thompson, 2022; van Hulst et al., 2025). This approach made it possible to use established concepts while still paying attention to new and unexpected insights from the case.

Two established frameworks were used to make sense of the empirical material. First, the AI readiness framework by Jöhnk et al. (2021) helped us look at the firm's preparedness across five areas: strategy, culture, organisation, technology and data.

It allowed us to see which areas were already in place, which still needed work, and how a small firm's more lightweight approach compared to the framework, which was originally developed with larger organisations in mind. Through this lens, elements such as the firm's simple policy ("AI-draft, human-decide"), its prompt library and its choice of tools could be seen as practical, scaled-down versions of strategic, cognitive and IT readiness.

Second, the framework by Enholm et al. (2022) was used to analyse outcomes and how value was created. It distinguishes between factors that support or hinder adoption, short-term effects such as better decisions and more efficient processes, and broader impacts on performance and sustainability. It also stresses that value comes not only from technology but from how it is combined with organisational capabilities and change management. Using this framework, we were able to link the firm's reported productivity gains, changes in error patterns and effects on well-being to the different dimensions of the model.

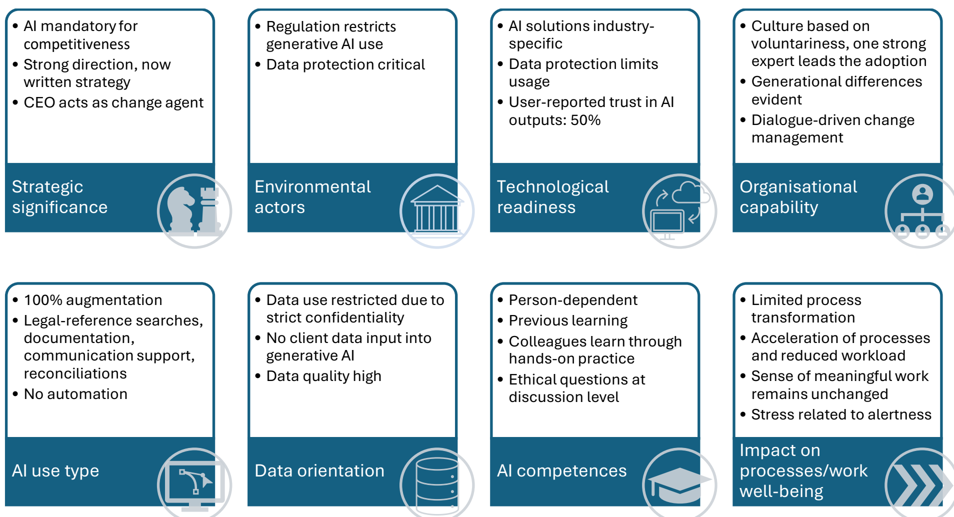

Figure 1: Theme categories in integrating AI into micro firm knowledge work
Source: Own

The analysis moved back and forth between the data and the theoretical frameworks. The interview transcript was first coded inductively, focusing on themes such as tasks, tools, workflows, outcomes and challenges. These themes were then compared with the concepts in the frameworks by Jöhnk et al. (2021) and Enholm et al. (2022), which helped to identify both matches and differences. From this process, eight theme categories were formed, as shown in Fig. 1: Strategic significance, Environmental actors, Technological Readiness, Organisational capability, AI use type, Data orientation, AI competences and Impact on processes/work well-being.

This study has some limitations. It focuses on a single case, relies on self-reported well-being, and productivity. The findings relate to one professional services micro-enterprise in a specific national context, so they should be applied to other settings with caution. However, the year-long follow-up and the use of established theoretical frameworks provide a solid basis for broader interpretation and further theory development (Yin, 2019).

4 Results

The results show that AI use in the micro-enterprise developed step-by-step over twelve months. Readiness was supported by simple governance practices and gradual upskilling, along with clearer data and processes that made tasks easier to handle with AI. Work was structured so that drafting and validation were kept separate, with humans responsible for checking outputs. Over time, AI outputs were gradually included in decision-making, with clear human checkpoints in place. The findings are presented in terms of productivity and efficiency, work well-being, and integration practices.

The firm has primarily implemented generative AI in the following areas: document drafting, templated email responses, client memos, and first-pass reconciliations of routine bookkeeping anomalies. Based on interview data rather than direct time measurement, the greatest gains were reported in preparatory work, with staff estimating notable time savings in drafting standard communications and some improvements in preparing checklists and workpapers. In contrast, core accounting judgments and final filings were human led, with AI providing alternative explanations for consideration. This distribution of labour was consistent with the thesis roadmap, which emphasised the removal of administrative friction from expert time while preserving human authority over compliance risk and client-specific nuances (Kemppainen, 2025).

These patterns reflect a shift in how tasks and decisions are organised. AI takes on most of the computational work, while humans focus on interpretation, context and ethical judgement. How well this works depends not only on the technology, but also on how workflows are redesigned and how clearly roles and responsibilities are defined (Jarrahi, 2018; Colson, 2019).

The firm's experience is similar to findings from other knowledge-intensive settings. In these contexts, generative AI has helped to speed up information creation and reduce managerial workload, but it still requires clear human oversight (Yurong, 2024).

It was observed that error patterns underwent a shift rather than a complete disappearance. The company reported a decrease in typographical and formatting errors, but occasional "plausible-but-wrong" statements were noted when prompts were ambiguous or when AI extrapolated outdated regulation. To reduce the risk of automation bias, the firm introduced an explicit "two-layer check" for outputs to external parties. This process was as follows: first, the drafter verified content against source documents; second, a risk-weighted review was applied for tax and compliance claims.

This response reflects the concept of readiness work, which places significant emphasis on governance, data quality, and transparent indicators for responsible adoption. It is also consistent with the literature on workforce management, which asserts the importance of maintaining human involvement in situations where the suitability of tasks for ML is only partial (Jöhnk et al., 2021; Brynjolfsson & Mitchell, 2017).

Based on interview data rather than measurable indicators, the effects on work-related well-being were mostly positive. Employees reported reduced deadline pressure and greater control over tasks, although prompt design and monitoring of AI errors remained initial stressors that eased over time. The mixed effects line up with earlier findings that AI can either reduce or increase strain depending on process design and maturity (Enholm et al., 2022).

4.1 Theoretical implications

The case shows that AI readiness in micro enterprises can develop in a simple, practice-based way rather than through a formal program, while still covering different aspects and evolving over time (Lokuge et al., 2019; Jöhnk et al., 2021; Pumplun et al., 2019). The findings also suggest that productivity and well-being improve when AI supports work step-by-step and humans remain in control through clear checkpoints (Jarrahi, 2018).

The case further shows a gradual move toward AI-supported workflows, where AI generates options and humans make the final decisions. This is in line with earlier research on AI-driven operating models and the role of governance in creating value (Colson, 2019; Iansiti & Lakhani, 2020; Enholm et al., 2022; Davenport, 2018). Together, these observations help describe how readiness and human-AI collaboration take shape in a small firm with limited resources and highlight the importance of clear checkpoints and governance in making AI use sustainable.

4.2 Practical implications

For managers in micro and small knowledge-work firms, the following steps offer a structured approach to AI adoption (see Fig.2).

Plan and select. Assess the current state and define strategic objectives (Sánchez et al., 2025). Use a concise readiness canvas to define use cases, expected outputs, verification rules, and data sources. This supports iterative and pragmatic AI adoption in SMEs (Horvat et al., 2023; Kemppainen, 2025; Weinberg, 2025). Managers can start with standardised, high-volume tasks and extend AI use gradually as skills and governance practices develop. Prioritise high-impact, low-complexity projects and choose the right tools and partners. (Agbaakin, 2025; Kemppainen, 2025; Longueville et al., 2025; Sánchez et al., 2025)

Pilot and evaluate. Start with small-scale pilots to validate AI before full implementation (Sánchez et al., 2025). Reduce automation bias by requiring source cues for AI-generated factual statements. This strengthens verification practices and supports responsible AI use. (Brynjolfsson et al., 2023; Enholm et al., 2022; Kemppainen, 2025) Define success metrics (KPIs) (Agbaakin, 2025).

Upskill and encourage. Embed learning into daily work using the "see one, do one, teach one" micro-training approach, and encourage a culture of experimentation and positive engagement with AI (Jöhnk et al., 2021; Kemppainen, 2025; Lokuge et al., 2019). Apply change-management practices that reduce resistance, clarify responsibilities and reinforce that AI is intended to augment rather than replace human capabilities. (Sánchez et al., 2025)

Measure and scale. Use KPIs to evaluate AI impact and scale accordingly (Sánchez et al., 2025).

These steps operationalise readiness and human-AI symbiosis principles associated with sustainable value creation (Davenport, 2018; Enholm et al., 2022; Jöhnk et al., 2021).

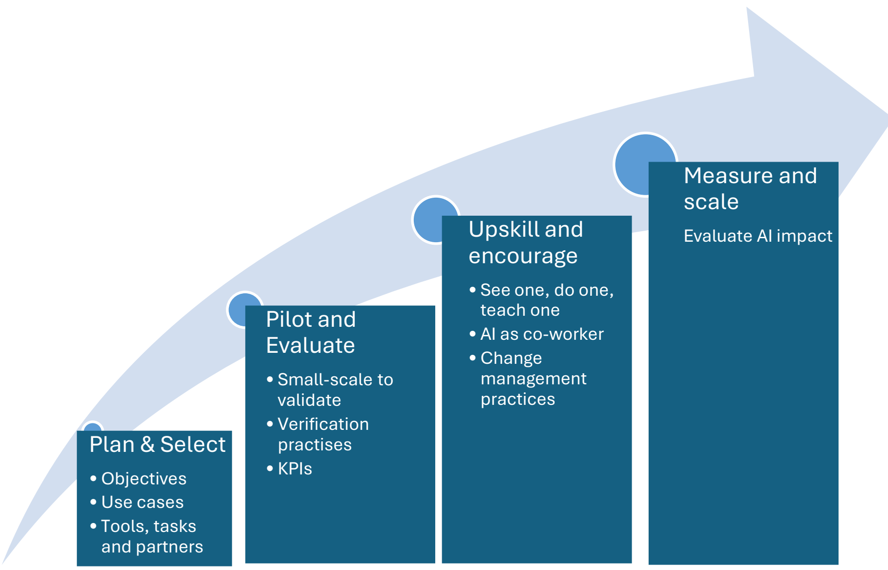

Figure 2: Approach to AI adoption in micro or small firms
Source: Own

5 Discussion and conclusions

The findings show that integrating AI into small-firm knowledge work is challenging yet achievable. The case shows that a small firm can improve efficiency by adopting AI gradually and with a human focus. This interpretation echoes workforce research that recognises major transformation without assuming simple substitution (Brynjolfsson & Mitchell, 2017) and with managerial guidance promoting a gradual, capability-based shift from analytics to AI (Davenport, 2018).

In our case, the micro-enterprise shows readiness in a practical way rather than through a formal program, while still achieving clear benefits. This supports the scalability of readiness (Lokuge et al., 2019) and relates with AI-specific readiness indicators (Jöhnk et al., 2021; Pumplun et al., 2019). It further suggests that lightweight mechanisms such as simple policies, prompt libraries, and customized tools can constitute functional readiness in resource-constrained contexts.

The case adds to human-AI collaboration research by showing how support roles can develop into more advisory roles, and how clear safeguards against automation bias help maintain trust and well-being (Jarrahi, 2018). It supports the proposition that AI-driven operating architectures can be realized incrementally in small firms when decision processing shifts are matched by clear human checkpoints (Colson, 2019; Iansiti & Lakhani, 2020). In this micro-enterprise context, data governance emerged as a central constraint. Data-related limitations shape feasible AI use cases more than technical capabilities do. A related observation is that data-driven innovation across European firms is strongly conditioned by concerns over fair data use, ecosystem governance and regulatory boundaries (Heikkilä et al., 2023).

Our case firm's move to AI-generated previews suggests that the evolutionary path observed in large enterprises (Davenport, 2018) is also achievable in micro-enterprises when governance, skills, and workflows develop in parallel. This contributes to emerging work on generative AI in professional services by illustrating how large-firm frameworks can be adapted to small-firm contexts (Russo, 2024; Sánchez et al., 2025; Weinberg, 2025).

Small knowledge-work firms can begin with high-volume, low-risk drafting tasks. Formalise "AI-draft, human-decide" as policy, standardise prompts, and measure cycle time. Gradually extend into advisory uses where AI proposes alternatives and explanations that humans evaluate. They should invest in data hygiene and documentation, require traceability for factual statements, and analyse AI mistakes to update prompts and checklists. These steps help connect high-level AI goals with everyday work.

The study has limitations. It is a single-case design in one national and professional context with self-reported productivity estimates and qualitatively assessed well-being effects, without direct quantitative measurement (e.g., time-tracking or validated well-being indicators). While single-case studies enable analytical generalization to theoretical propositions (Yin, 2019), the findings' transferability to other sectors, firm sizes, or cultural contexts requires empirical validation. Future research should therefore validate these findings using quantitative approaches, such as time-and-motion studies, digital-trace data, or standardized well-being measures, in addition to examining how the assistive-to-advisory pattern of human-AI collaboration differs across sectors and how specific readiness subdimensions influence outcomes in micro-enterprises. It should also explore how the minimal readiness bundle scales as firms grow or adapt to changing regulations such as the EU AI Act (European Union, 2024) and clarify construct boundaries by linking digital-innovation readiness with AI-readiness frameworks (Lokuge et al., 2019; Jöhnk et al., 2021; Pumplun et al., 2019).

Effective AI integration in small-firm knowledge work is mainly an organisational design task. Building a minimal readiness bundle, dividing work so that humans and AI each use their strengths, and adding safeguards against automation bias allow firms to improve productivity and efficiency without harming well-being. This case shows that such progress is achievable even with limited resources when adoption is deliberate, iterative and human-centred.

Endnote

The authors acknowledge the use of artificial intelligence tools in supporting the literature search, improving the English language and formulation of the text, and assisting in the proofreading of the manuscript.

Acknowledgment

This publication is part of the project AIRA – AI Solutions for Sustainable and Productive Knowledge Work, co-funded by the European Union. The authors would like to especially thank Antti Rimpiläinen (Kajaani University of Applied Sciences) and Mira Kekkonen (Oulu University of Applied Sciences) for their contributions to identifying relevant literature.

Co-funded by
the European Union

References

Agbaakin, O. (2025). Leveraging Artificial Intelligence as a Strategic Growth Catalyst for Small and Medium-sized Enterprises. Computers and Society. Cornell University. https://doi.org/10.48550/arXiv.2509.14532

Åström, J., Reim, W., & Parida, V. (2022). Value creation and value capture for AI business model innovation: A three-phase process framework. Review of Managerial Science, 16(7), 2111–2133. https://doi.org/10.1007/s11846-022-00521-z

Brynjolfsson, E., Li, D., & Raymond, L. R. (2023). Generative AI at work (NBER Working Paper No. 31161). National Bureau of Economic Research. https://doi.org/10.3386/w31161

Brynjolfsson, E., & Mitchell, T. (2017). What can machine learning do? Workforce implications. Science, 358(6370), 1530–1534. https://doi.org/10.1126/science.aap8062

Cheong, B.C. (2024). Transparency and accountability in AI systems: safeguarding wellbeing in the age of algorithmic decision-making. Front. Hum. Dyn. 6:1421273. doi: 10.3389/fhumd.2024.1421273

Colson, E. (2019). What AI-driven decision making looks like. Harvard Business Review. https://hbr.org/2019/07/what-ai-driven-decision-making-looks-like

Davenport, T. H., Jarvenpaa, S., & Beers, M. (1996). Improving knowledge work processes. MIT Sloan Management Review, Summer 1996.

Davenport, T. H. (2018). From analytics to artificial intelligence. Journal of Business Analytics, 1(2), 73–80. https://doi.org/10.1080/2573234X.2018.1543535

De Longueville, B., Sanchez, I., Kazakova, S., Luoni, S., Zaro, F., Daskalaki, K., & Inchingolo, M. (2025). The Proof Is in the Eating: Lessons Learnt from One Year of Generative AI Adoption in a Science-for-Policy Organisation. AI, 6(6), 128. https://doi.org/10.3390/ai6060128

Enholm, I. M., Papagiannidis, E., Mikalef, P., & Krogstie, J. (2022). Artificial intelligence and business value: A literature review. Information Systems Frontiers, 24(5), 1709–1734. https://doi.org/10.1007/s10796-021-10186-w

European Commission. (2003). SME definition. Internal Market, Industry, Entrepreneurship and SMEs. https://single-market-economy.ec.europa.eu/smes/sme-fundamentals/sme-definition_en

European Union. (2024). Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024 laying down harmonised rules on artificial intelligence (Artificial Intelligence Act). Official Journal of the European Union, L 2024/1689, 1–258. https://eur-lex.europa.eu/eli/reg/2024/1689/oj/eng

Fan, X., Soomro, M. A., Soomro, S. A., Sohu, J. M., & Shah, N. (2025). Artificial intelligence adoption and technostress in manufacturing SMEs. Journal of Manufacturing Technology Management. https://doi.org/10.1108/jmtm-02-2025-0120

Heikkilä, M., Ahmad, F., & Heikkilä, J. (2023). Unlocking the potential of data-driven business models: An empirical investigation into the role of ecosystems and fair data use. Bled eConference Proceedings. https://doi.org/10.18690/um.fov.6.2023.6

Horvat, D., Kroll, H., & Jäger, A. (2023). AI readiness: An integrated socio-technical framework. In HCI International 2023 Posters (pp. 539–546). Springer. https://doi.org/10.1007/978-3-031-36121-0_69

Iansiti, M., & Lakhani, K. R. (2020). Competing in the age of AI: Strategy and leadership when algorithms and networks run the world. Harvard Business Review Press.

Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human–AI symbiosis in organizational decision making. Business Horizons, 61(4), 577–586. https://doi.org/10.1016/j.bushor.2018.03.007

Jöhnk, J., Weißert, M., & Wyrtki, K. (2021). Ready or not, AI comes—An interview study of organizational AI readiness factors. Business & Information Systems Engineering, 63(1), 5–20. https://doi.org/10.1007/s12599-020-00676-7

Kemppainen, H. (2025). Utilizing Artificial Intelligence in the Expert Work of a Small Accounting Firm. Master's thesis. Kajaani University of Applied Sciences.

Lokuge, S., Sedera, D., Grover, V., & Xu, D. (2019). Organizational readiness for digital innovation: Development and empirical calibration of a construct. Information & Management, 56(3), 445–461. https://doi.org/10.1016/j.im.2018.09.001

Mohd Rasdi, R., Umar Baki, N. (2025). Navigating the AI landscape in SMEs: Overcoming internal challenges and external obstacles for effective integration. PLOS ONE 20(5): e0323249. https://doi.org/10.1371/journal.pone.0323249

Neumann, O., Guirguis, K., & Steiner, R. (2022). Exploring artificial intelligence adoption in public organizations: A comparative case study. Public Management Review, 26(1), 114–141. https://doi.org/10.1080/14719037.2022.2048685

Nevi, G., Pizzichini, L., Bastone, A., & Dezi, L. (2025). Adoption of artificial intelligence by micro and small health enterprises: effects of entrepreneurial orientation on the TOE model. European Journal of Innovation Management, Emerald Group Publishing Limited, vol. 28(11), pp. 209-241.

OECD. (2023). The impact of AI on the workplace: Evidence from OECD case studies of AI implementation. OECD Publishing. https://doi.org/10.1787/2247ce58-en

Oluwamola, O., Adekunle, A., & Ogunleye, B. (2025). Business transformation through AI adoption in agile enterprises: Design methodologies, architectures, deployment scenarios, governance, and future directions. International Journal of Scientific Research and Management, 13(3), 1–18. https://doi.org/10.18535/ijsrm/v13i03.ec07

Pumplun, L., Tauchert, C., & Heidt, M. (2019). A new organizational chassis for artificial intelligence: Exploring organizational readiness factors. In Proceedings of the 27th European Conference on Information Systems (ECIS).

Radhakrishnan, R., Duan, Y., & Soylu, A. (2022). Understanding organizations' artificial intelligence journey: A qualitative approach. Pacific Asia Journal of the Association for Information Systems, 14(6), 1–34. https://doi.org/10.17705/1pais.14602

Russo, D. (2024). Navigating the complexity of generative AI adoption in software engineering. ACM Transactions on Software Engineering and Methodology, 33(6), Article 154. https://doi.org/10.1145/3652154

Sánchez, E., Calderón, R., & Herrera, F. (2025). Artificial intelligence adoption in SMEs: Survey based on TOE–DOI framework, primary methodology and challenges. *Applied Sciences, 15*(12), 6465. https://doi.org/10.3390/app1512646

Soomro, B. A., Fan, X., Sohu, J. M., Soomro, S. A., & Shaikh, F. A. (2024). Organizational support and AI-related anxiety in SMEs. *Kybernetes*. https://doi.org/10.1108/k-07-2024-1889

Soulami, B., Benchekroun, H., & Galiulina, E. (2024). Human-centered AI adoption and worker productivity: A systematic review. *Frontiers in Artificial Intelligence*. https://doi.org/10.3389/frai.2024.1473872

Thompson, J. (2022). A Guide to Abductive Thematic Analysis, *The Qualitative Report,* vol. 27, no. 5, pp. 1410-1421.

Uren, V., Edwards, J. S., & Jiménez, A. (2023). Technology readiness and the organizational journey towards AI adoption: An empirical study. International Journal of Information Management, 68, Article 102588. https://doi.org/10.1016/j.ijinfomgt.2022.102588

van Hulst, Merlijn, & E. L. Visser. (2025). Abductive Analysis in Qualitative Research. Public Administration Review 85(2), pp. 567–580.

Wahab, M. D. A., & Radmehr, M. (2024). The impact of AI assimilation on firm performance in small and medium-sized enterprises. *Heliyon, 10*(8), e29580. https://doi.org/10.1016/j.heliyon.2024.e29580

Weinberg, B. D. (2025). A framework for the adoption and integration of generative AI in midsize organizations and enterprises (FAIGMOE). Journal of Business Research, 170, 114–128.

Yang, L., Holtz, D., Jaffe, S., Suri, S., Teevan, J., Iqbal, S., & Horvitz, E. (2024). Artificial intelligence adoption in a professional service industry: A multiple case study. Technological Forecasting and Social Change, 199, Article 123251. https://doi.org/10.1016/j.techfore.2024.123251

Yin, R. K. (2019). Case study research and applications: design and methods (Sixth edition). SAGE.

Yurong, C. (2024). Unlocking SME potential. In AI and Business Innovation (pp. 45–62). CRC Press. https://doi.org/10.1201/9781003469551-2