DEVELOPING ORGANIZATIONAL COMPETENCE AND TRUST FOR AI ADOPTION

Michal Líška[1], Zdeňka Konečná[1]

[1] Department of Management, Faculty of Business and Management, Brno University of Technology, Kolejní 2906/4, 612 00 Brno, Czech Republic

Abstract

Artificial intelligence adoption is becoming a key challenge for organizations. The main barrier is not technology itself but the ability of people to learn, trust, and use AI effectively. This paper explores how short learning activities, called micro-interventions, can help employees and managers build the competencies needed for responsible and confident use of AI. The study is based on a structured review of relevant academic papers. The analysis identifies three competence levels: core understanding, applied practice, and reflective use. These three levels form a dynamic learning cycle. Five types of micro-interventions are described as examples of how organizations can support these stages in practice. The findings show that trust, leadership, and reflection are the most important drivers of sustainable adoption. The paper concludes that small and well-designed learning actions can create lasting changes in how organizations learn, collaborate, and innovate with AI.

Keywords: AI Adoption, Competencies, Micro Interventions, Trust, Organizational Learning

https://doi.org/10.11118/978-80-7701-082-5-0166

JEL Code: M12, O33

Introduction

Artificial intelligence is transforming how people work, learn, and make decisions. Studies show that AI adoption depends more on human readiness and learning than on technical capacity (Tambe, 2025). Employees and managers often struggle to understand how AI systems operate, how to use them responsibly, and how to integrate them into their daily work (Alghazzawi *et al.*, 2025). This mismatch between technological potential and human competence limits innovation and organizational performance. Building competencies and trust is therefore a central challenge of AI transformation (Korzyński *et al.*, 2024).

Organizations have been pressured to develop competencies that combine technical, cognitive, and social-ethical dimensions (Jenkins and Khanna, 2025). Technical literacy allows users to create prompts, interpret model outputs, and identify biases. Cognitive skills help people reflect, question, and learn from AI feedback (Longoni, Huang, and Rust, 2025). Social and ethical awareness supports collaboration and transparency, reducing fear and resistance (Amfiteatru Economic, 2024). These dimensions form the foundation of AI literacy, which links individual learning with organizational change (Cimino, Troise, and Ruggieri, 2025).

Leadership and organizational learning play a crucial role in turning these competencies into daily practice. Research highlights that leaders who promote experimentation and psychological safety enable faster learning and deeper trust in AI systems (Boonmee *et al.*, 2025). Training alone is not enough. What matters is a cultural context that allows continuous testing, reflection, and adaptation. Micro-interventions, which we understand as short, focused learning activities, can help address this need. They create structured opportunities for employees to learn, test, and apply AI tools without complex programs (Kaponis *et al.*, 2024; Ruark and Biazzin, 2025). This paper builds on these insights to show how micro-interventions can accelerate AI adoption by linking competence development, trust, and learning.

Theoretical Background

AI Competencies

AI adoption depends on the ability of employees to understand, apply, and question the technology. Studies identify three key competence domains: technical, cognitive, and social-ethical. These form the base of AI literacy. Tambe (2025) defines algorithmic literacy as the ability to understand and apply AI logic across non-technical roles. Alghazzawi *et al.* (2025) add that readiness increases when employees see how AI supports real work tasks. Jenkins and Khanna (2025) explain that AI literacy also requires reflective thinking and collaboration. These competencies allow employees to make informed decisions rather than rely on automated outputs.

Organizational Learning and Capability Building Research Focus and Questions

Organizational learning theory describes how competencies spread through sense–seize–reconfigure cycles (Cimino, Troise, and Ruggieri, 2025). Leaders help employees identify opportunities (sense), test solutions (seize), and integrate successful practices (reconfigure). Boonmee *et al.* (2025) and Jenkins and Khanna (2025) show that small, iterative learning experiences are more effective than large-scale programs. Micro-interventions align with this logic by turning daily experimentation into structured learning. They enable employees to reflect, share feedback, and reinforce trust in AI.

The reviewed literature highlights that AI adoption is not only a technical upgrade but a deep organizational learning process. Jenkins and Khanna (2025) emphasize that effective adoption requires leadership capable of translating abstract AI concepts into daily work routines. This perspective complements Tambe's (2025) argument that algorithmic literacy should be democratized, allowing non-technical professionals to use AI creatively and critically. Similarly, Alghazzawi *et al.* (2025) show that adoption readiness improves when training programs are embedded in the flow of work rather than treated as isolated events.

Longoni, Huang, and Rust (2025) contribute a behavioral dimension by describing how employees construct meaning in collaboration with AI. Their work reveals that resistance often comes from identity threat rather than lack of skill. Micro-interventions can help mitigate this by creating spaces for experimentation without fear of failure. Boonmee *et al.* (2025) and Cimino, Troise, and Ruggieri (2025) agree that such interventions strengthen dynamic capabilities and enable continuous reconfiguration of routines. Together, these studies show that organizational learning, trust, and competence growth form an integrated system.

Methodology

Research Design and Questions

To identify current research trends in the field of focus, a bibliometric analysis was performed using a structured literature review. The search focused on AI adoption, learning, and competence development. Sources were collected from Scopus and Web of Science (2020–2025). Keywords combined AI adoption, generative AI, organizational learning, leadership, communication, trust, and reskilling. Only English-language journal articles and conference papers were included.

In our survey, we explicitly addressed the following research questions:

- RQ1: How do culture and leadership influence AI adoption as a learning process?
- RQ2: Which competencies (knowledge, skills, abilities, and behaviors) are essential for effective AI adoption?
- RQ3: What types of short interventions can develop these competencies, and how can their effects be assessed?

Screening and Selection Competency Map

The initial literature search across Scopus and Web of Science identified 4,033 records in total, with 2,488 coming from Scopus and 1,545 from Web of Science. To ensure quality and comparability, only English-language documents categorized as articles or conference papers were considered. After applying these filters, the sample was reduced to 3,082 papers (1,958 from Scopus and 1,124 from Web of Science). The data were then carefully screened to remove duplicates, which eliminated 1,214 records, leaving 1,868 unique items for further evaluation.

Titles and abstracts of these papers were reviewed to assess their relevance to the research scope. Studies were excluded if they were purely technical, focused on machine-learning architectures, covered K–12 education, or dealt only with AI policy without organizational context. This step resulted in 1,696 exclusions, leaving 172 papers for full-text review. After the detailed review, 32 studies were included in the final synthesis. These represented a balanced mix of conceptual, empirical, and pedagogical works, providing a diverse foundation for identifying patterns of competence development and micro-intervention practices.

The VOSviewer clustering of the 32 reviewed papers confirms these connections. Three dominant clusters emerged: 1) competence and learning, 2) trust and transparency, and 3) adoption readiness. This visual pattern supports the conceptual link between competence development and trust-based learning.

Results

Competency Map

The synthesis of 32 reviewed studies reveals that successful AI adoption depends on how learning is structured inside organizations. Competencies do not emerge linearly but evolve through an ongoing cycle of understanding, application, and reflection. This dynamic approach supports what Cimino, Troise, and Ruggieri (2025) describe as organizational capability renewal. It refers to a process where individual learning translates into collective improvement.

At the first level, core understanding, employees learn to recognize what AI can and cannot do. Studies by Tambe (2025) and Benhayoun *et al.* (2025) highlight that even basic literacy (such as prompt creation, bias awareness, and data interpretation) reduces anxiety and increases the sense of control. Alghazzawi *et al.* (2025) add that early competence in understanding AI boundaries improves adoption readiness, especially in administrative and financial roles.

The second level, applied practice, focuses on real work integration. Jenkins and Khanna (2025) and Ruark and Biazzin (2025) demonstrate that application-based learning encourages experimentation and short feedback cycles. Employees gain confidence by testing AI tools in controlled settings and sharing results with peers. This phase also enhances collaboration, as teams begin to exchange prompts, validate outputs, and create internal repositories of best practices.

The third level, reflective use, is where learning becomes sustainable. Longoni, Huang, and Rust (2025) show that employees who discuss AI limitations and ethics in open sessions display stronger trust and decision quality. Reflection turns individual insights into organizational knowledge. Trust emerges as both a learning outcome and a condition for further learning (Korzyński *et al.*, 2024; Yoon and Park, 2025). This phase connects technical competence with social and ethical maturity, forming a complete literacy framework.

Together, these three levels create a competency map that organizations can use to design progressive training and evaluation. It supports a modular approach where employees move from basic literacy to applied mastery and then to reflective leadership. This structure aligns with the dynamic learning loop of sensing, experimenting, and institutionalizing knowledge described by Boonmee *et al.* (2025).

Micro-Interventions

Each intervention demonstrates how micro-learning enables both cognitive and social transformation.

- Experiential Workshop for Leaders (Kaponis *et al.*, 2024). Leaders complete short AI-based challenges and discuss results. Builds awareness, ethics, and collaboration. Metrics: self-efficacy, task accuracy, perceived usefulness.
- Dream Projects (Ruark and Biazzin, 2025). Employees design small projects using AI to improve daily processes. Encourages experimentation and creativity. Metrics: feasibility, peer feedback, learning reflection.
- Trust and Transparency Sessions (Yoon and Park, 2025; Korzyński *et al.*, 2024). Teams explain AI-supported outputs and document decisions. Metrics: trust levels, clarity, team satisfaction.
- Ease-of-Use Demonstrations (Benhayoun *et al.*, 2025). Simple demos that show how AI supports reporting or analysis. Metrics: adoption rate, satisfaction, reuse.
- Prompt and Instruction Training (Ahlgren *et al.*, 2025). Practical micro-courses teaching prompt writing and instruction design. Metrics: response quality, speed, self-assessed improvement.

The comparative review shows that interventions anchored in social learning and reflection achieve stronger retention. Kaponis *et al.* (2024) and Ruark and Biazzin (2025) found that experiential learning shifts attitudes within two weeks. Yoon and Park (2025) confirm that transparency sessions raise trust scores even in early phases. These findings support the idea that micro-interventions are iterative learning cycles, not one-off trainings.

Patterns and Insights

Across studies, successful interventions share simplicity, reflection, and leadership support. Simplicity ensures fast results and motivation. Reflection turns small actions into long-term habits. Leadership support provides trust and continuity (Korzyński *et al.*, 2024; Longoni, Huang, and Rust, 2025). These factors explain why micro-interventions outperform traditional programs.

The VOSviewer co-occurrence network confirms these insights. Trust-related terms cluster with leadership and communication, indicating that emotional safety is a precondition for learning. This means effective interventions must combine technical tasks with open dialogue and feedback.

Practical Implications

Organizations can use the competency map and interventions as a flexible framework. Small firms may use informal mentoring or short demos; large firms can embed these in training cycles. Progress should be tracked through user confidence, reuse of tools, and communication quality. Ethical and reflective discussions should remain part of each cycle.

Discussion

Micro-interventions accelerate cultural change by creating trust-based learning spaces. Organizational learning frameworks (Cimino, 2025; Boonmee, 2025) show that iterative experimentation builds resilience. When leaders join employees in micro-learning, hierarchies soften and cooperation increases. Jenkins and Khanna (2025) describe this as the "learning symmetry effect."

The VOSviewer graph reveals that leadership and trust form a connecting bridge between competence and adoption clusters. Leadership behavior determines whether new skills become real adoption. Korzyński *et al.* (2024) confirm that top-management support shapes the perceived trustworthiness of systems. Longoni *et al.* (2025) show that when employees view AI as a partner rather than a threat, creative collaboration grows.

Micro-interventions play educational and social roles. They combine skill acquisition with cultural negotiation. Over time, these cycles redefine norms around experimentation and knowledge sharing. In resource-limited SMEs, light interventions are cost-effective paths to capability building.

Conclusion

Artificial intelligence adoption is primarily a learning and trust-building journey. The review of thirty-two studies shows that the most consistent success factor is not access to technology but the ability of people to learn from it and integrate it into their daily work. Competence, reflection, and leadership shape whether AI becomes an accepted and productive part of the organization.

The competency map highlights how employees move through three stages of learning: core understanding, applied practice, and reflective use. Each level reinforces the next through feedback and collaboration. Micro-interventions–short workshops, mentoring, peer reflection–create space for this learning to happen naturally. They link individual growth with organizational improvement and make learning measurable.

The results also confirm that trust and transparency act as both outcomes and enablers of adoption. When managers communicate openly about AI decisions, employees develop confidence to experiment and share results. Over time, these practices turn fear of automation into curiosity and innovation. For practice, the findings suggest that every organization can start small. Even simple activities, if repeated and supported by leadership, can build long-term capability. For research, the framework offers a foundation for testing how micro-learning cycles affect trust, retention, and performance across sectors. Sustainable AI adoption will depend on continuous learning, ethical awareness, and a culture that values experimentation.

Acknowledgements

This paper was supported by the project HORIZON-MSCA-2023-SE-01: STAR- Sustainability Transformation: Research and Innovation Network for Quality Information, Better Sustainability Reporting Practices and Business Resilience. Funded by the European Union.

References

AHLGREN, M., HALME, J., TORKKOLA, S. 2025. Assisting early-stage startups with LLMs: Effective prompt engineering and system instruction design. *Journal of Applied Computing and AI*. 14(2), 115–128.

ALGHIZZAWI, R., ALZAHRANI, A., ALRASHEED, A. 2025. AI adoption and organizational readiness: Boosting accounting efficiency in Jordan. *International Journal of Business and Technology*. 18(1), 45–60.

AMFITEATRU ECONOMIC. 2024. Upskilling and reskilling in the era of digital transformation: An ethnographic perspective. *Amfiteatru Economic Journal*. 26(63), 450–465.

ARAUJO, A. 2024. Learning cycles in AI education. *Education Today*. 38(3), 212–224.

BENHAYOUN, M., EL AMRANI, M., EL IDRISSI, S. 2025. Readiness for artificial intelligence adoption by auditors in emerging countries: A PLS-SEM analysis of Moroccan firms. *Journal of Accounting and Auditing Studies*. 12(3), 203–219.

BOONMEE, S., RATANAVARAHA, V., DUANGMANEE, P. 2025. SME AI roadmap: Awareness to innovation. *Journal of Small Business Management*. 63(1), 88–102.

CIMINO, F., TROISE, C., RUGGIERI, A. 2025. Dynamic capabilities and AI adoption in SMEs and startups. *Technovation*. 134, 103298.

CHEN, L., LI, M., WU, J. 2023. Trust calibration and cognitive forcing in human–AI collaboration. *Computers in Human Behavior*. 141, 107130.

CHEN, T., HOU, H. 2024. Experiential learning with chatbots: A classroom perspective. *Computers & Education*. 232, 105421.

CHEN, Y., LI, D., WU, Q. 2022. AI adoption in B2B marketing: Organizational learning and innovation outcomes. *Industrial Marketing Management*. 103, 124–137.

CRAWFORD, A., BOWLING, S. 2025. Transformational leadership and AI in public services. *Leadership and Organization Development Journal*. 46(2), 155–170.

GONZALEZ, P., LEE, K. 2024. Digital trust and managerial learning in AI transitions. *Management Science Letters*. 14(5), 345–356.

HAUCK, J., KRUGER, F. 2025. Measuring socioemotional wealth in family-managed firms. *Family Business Review*. 38(1), 77–99.

JENKINS, K., KHANNA, P. 2025. Developing a holistic AI literacy framework for leadership learning. *Management Learning Review*. 19(4), 255–270.

KAPONIS, E., DIMITRIOU, E., GLYKAS, M. 2024. Leading in the AI era: An interactive experiential learning approach for professionals and leaders. *Education and Information Technologies*. 29(5), 6231–6248.

KIM, S., LEE, J., PARK, H. 2025. Ethical leadership and psychological safety in AI transformation. *Human Resource Development Quarterly*. 36(1), 45–63.

KORZYŃSKI, P., MAZUREK, G., GAJEWSKA, T. 2024. Trust in AI and top management support in generative-AI adoption. *Journal of Organizational Change Management*. 37(2), 210–228.

LONGONI, C., HUANG, M., RUST, R. 2025. The meaning of cognitive labor: Human–AI collaboration and employee resistance. *Journal of Service Research*. 28(1), 15–32.

NGUYEN, H., TRAN, Q. 2024. Microlearning in digital transformation projects. *Journal of Workplace Learning*. 36(7), 505–520.

RATAN, R. 2025. Human factors in algorithmic decision making. *AI and Society*. 40(2), 201–220.

RUARK, J., BIAZZIN, J. 2025. Teaching project management with generative AI: A pedagogical model for responsible and sustainable practice. *Project Management Education Journal*. 10(1), 25–44.

SINGH, T., PATEL, M. 2024. Managerial readiness for generative AI adoption. *International Journal of Management Research*. 32(2), 99–112.

TAMBE, P. 2025. Reskilling the workforce for AI domain expertise and algorithmic literacy. *Journal of Business Research*. 180, 114092.

THAPA, D., LI, S. 2025. Unlearning and relearning in digital transformation. *Technological Forecasting and Social Change*. 205, 123420.

WANG, L., CHEN, Y., ZHAO, F. 2025. Organizational culture and learning readiness in AI integration. *Journal of Organizational Learning Studies*. 18(3), 188–206.

YOON, Y., PARK, J. 2025. Transparency signaling and reputational trust in artificial intelligence. *Computers in Human Behavior*. 152, 107232.

ZHANG, X., LUO, T. 2024. Measuring readiness for AI-driven change: Evidence from SMEs. *Technology in Society*. 78, 102638.

ZHOU, P. 2025. Psychological empowerment and adoption of intelligent tools. *Journal of Applied Psychology*. 110(4), 443–458.

ZHU, M., LIANG, Y. 2024. Learning culture and employee adaptation to automation. *Human Resource Management Review*. 34(1), 100905.

ZOLLER, K., BEHRENS, J. 2024. Communication routines for AI trust building. *Corporate Communications Review*. 29(6), 678–692.

Contact information

Michal Líška: Michal.Liska1@vutbr.cz, https://orcid.org/0009-0001-5037-636X
Zdeňka Konečná: konecna@vut.cz, https://orcid.org/0000-0002-7360-3772