Preparing Future-Ready Workers: A Framework for Classifying Organizational AI Use Cases and Skills Gaps

Claudia Hess[1], Cornelia Heinisch[1], Sibylle Kunz[1] and Adrienne Steffen[2]
[1]Department of IT & Engineering, IU International University of Applied Sciences, Erfurt, Germany
[2]Department of Management, IU International University of Applied Sciences, Erfurt, Germany

claudia.hess@iu.org
cornelia.heinisch@iu.org
sibylle.kunz@iu.org
adrienne.steffen@iu.org

Abstract: Artificial intelligence (AI) is reshaping how organizations create value and how employees contribute across the value chain. Existing AI literacy and competency frameworks, however, often remain too general to specify which competencies are needed in concrete organizational use cases. This study develops and applies the AI Future-Job-Readiness and Reskilling Framework, which links three dimensions: the organizational location of AI use in the value chain, the value-creation profile of the AI use case, and the cognitive demands placed on workers based on the revised Bloom's taxonomy. The empirical basis consists of 14 semi-structured in-depth interviews with managers holding leadership responsibilities and subject-matter experts across diverse industries in Germany. Across these interviews, 27 organizational AI use cases were identified, spanning everyday support tasks to more advanced forms of AI-enabled process support. This range shows that AI use differs not only in the tools applied, but also in the kind of work it supports and the responsibilities it leaves with employees. The use cases were mapped onto the proposed framework to identify where AI creates value within the firm, what type of cognitive work is being augmented or transformed, and which classes of AI tools are deployed. Two contrasting cases were analyzed in depth to illustrate the framework's application. The analysis shows that competency requirements cannot be derived from AI tools alone. Instead, they depend on how AI contributes to value creation, where it is embedded in organizational activity, and which human responsibilities remain in the work process. A central finding is that higher-order cognitive demands often concern evaluating AI-generated outputs against domain-specific criteria, rather than technically assessing AI systems themselves. The study's main contribution is a conceptual framework, refined through the analysis of selected use cases, that translates organizational AI adoption into targeted upskilling needs and guides the alignment of competence development with AI-enabled work environments.

Keywords: Artificial intelligence, AI value creation, Framework, Future ready workers, Skills

1. Introduction to AI-induced Change in the Workforce

The rapid integration of artificial intelligence (AI) into organizational workflows is fundamentally altering how employees contribute to value creation by automating routine processes (Murire, 2024) and is adopted across organisational functions (Aguado-García et al., 2026). AI applications increasingly augment or automate tasks across all organizational functions. As a result, employees must operate new tools, adapt work practices, evaluate AI-generated outputs, and take responsibility for AI-supported decisions. This development creates a growing need for workforce upskilling. The *Future of Jobs Report 2025* reports that 63% of employers consider skill gaps a major barrier to business transformation by 2030, while 85% plan to invest in upskilling their workforce (World Economic Forum, 2025, p. 6). These developments require more targeted workforce strategies. Future-ready employees are those who can meet these demands and work productively in AI-enabled environments. This aligns with dynamic capabilities, defined as “the sensing, seizing, and transforming needed to design and implement a business model” (Teece, 2018, p. 43). Firms need such capabilities to remain productive and resilient (Teece, 2018). Future-readiness therefore means using new technologies, recognizing opportunities, adapting work practices, and supporting organizational transformation.

AI literacy and competency frameworks offer useful starting points for defining future-readiness. But targeted upskilling requires translating these broad perspectives into specific requirements. Organizations implement AI through concrete use cases in specific processes, value-chain activities, and employee roles. The key question is which competencies specific AI-supported tasks and contexts require. This paper addresses this challenge by developing and applying the AI Future-Job-Readiness and Reskilling Framework for classifying organizational AI use cases and deriving workforce-relevant competency implications. Empirically, the study is based on 14 semi-structured interviews with managers and subject-matter experts from German organizations. The interviews identified 27 organizational AI use cases across different industries and functions, which were categorized into the framework. Two contrasting cases illustrate how to translate AI use cases into targeted upskilling needs.

The paper is structured as follows. Section 2 develops the conceptual foundation and introduces the AI Future-Job-Readiness and Reskilling Framework. Section 3 outlines the study design, sample, data collection, and analysis. Section 4 classifies selected organizational AI use cases in the framework, derives competency implications, and discusses its analytical usefulness and limitations. Section 6 concludes with key findings and directions for future research.

2. Literature Review and Framework Development

This section develops the conceptual foundation by discussing AI-related skill requirements, introducing the framework dimensions, and integrating them into the AI Future-Job-Readiness and Reskilling Framework.

2.1 Future-ready Employees and AI-related Skill Gaps

As organizations integrate sophisticated automation, firms increasingly demand AI literacy, defined as "a set of competencies that enables individuals to critically evaluate AI technologies; communicate and collaborate effectively with AI; and use AI as a tool online, at home, and in the workplace" (Long and Magerko, 2020, p. 2). AI literacy therefore represents a foundational layer of future-readiness: it enables employees to operate AI systems, and to assess their outputs, limitations and biases to ensure appropriate use and should not be understood as technical proficiency alone. Human-centered competencies, such as emotional intelligence, ethical judgment, and complex problem-solving, form part of what makes AI use meaningful and responsible in organizational and societal settings (Long and Magerko, 2020, Murire, 2024).

Labor market analyses reflect this emphasis. The World Economic Forum's Future of Jobs Report 2025 identifies analytical thinking, resilience, leadership, social influence, and creative problem-solving among the skills expected to remain critical as AI and automation increasingly transform work environments (World Economic Forum, 2025, pp. 39–40). Similarly, the AI Literacy Framework for Primary and Secondary Education (OECD and European Union, 2026) and UNESCO's AI Competency Framework for Students (UNESCO, 2024), include both AI knowledge and human-centered capabilities. Similarly, current literacy scales emphasize dimensions like basic operational skills, prompt engineering ability, quality evaluation ability, innovative application ability and compliance and ethical awareness (Liu et al. 2025). AI-related skill gaps thus extend beyond technical competencies. In organizational settings, broad AI literacy perspectives must be translated into role-, task-, and use-case-specific competency requirements. Higher education institutions must therefore understand these AI-driven shifts in workplace competency requirements and adapt their curricula accordingly to prepare graduates for AI-enabled work environments (Chinoracky et al. 2026). This motivates a framework that links organizational AI use cases to workforce-relevant competency demands.

2.2 Framework Dimensions for Linking Organizational AI use Cases to Workforce Competencies

The following subsections develop the analytical dimensions for classifying organizational AI use and associated AI competencies. Its unit of analysis is the organizational AI use case, understood as the use of one or more AI tools within a specific work process for a defined purpose. This matters because the same AI tool can require different competencies across uses, while one use case may combine several tools. The framework therefore captures three aspects of each AI use case: its organizational context, its contribution to the work process, and the cognitive demands placed on workers.

2.2.1 The value chain

The value chain describes the activities a firm performs to design, produce, market, deliver, and support its products or services (Porter, 1985). It distinguishes primary activities, such as inbound logistics, from support activities, such as human resources. Each stage is intended to add value to the final output Management activities control these core and support processes. The value chain locates *where* AI creates value within the firm, and indicates which roles, functions, or employee groups may require upskilling. Some AI applications remain localized within one function (e.g., predictive maintenance in production), while others, such as enterprise-wide copilots, cut across activities and create broader upskilling needs.

2.2.2 Value-creation profile of AI use cases

To specify what kind of contribution AI makes to the work process, existing AI classifications provide useful reference points, but they are typically designed for purposes other than workforce-oriented analysis. The most prominent is the OECD Framework for the Classification of AI System with the five dimensions People & Planet, Economic Context, Data & Input, AI Model, and Task & Output (OECD, 2022). It supports policymakers in characterizing and governing AI systems, particularly regarding risk, transparency, and accountability. For this

study, the most relevant dimension is Task & Output, which captures a system's technical function and output, such as recognition, forecasting, personalization, or goal-driven optimization. However, this remains a system-level description, neither showing organizational purpose nor the cognitive work it reshapes. The AI Methods, Capabilities and Criticality Grid (AI-MC²), proposed by Schmid et al. (2021), classifies AI applications by AI methods used, implemented capabilities, and the level of criticality. It is a practical classification scheme to support norms, standards, compliance, and the comparison of AI applications. Both classification schemes therefore provide useful orientation, but not the workforce-oriented distinction required here.

To capture this missing perspective, we introduce the value-creation profile of AI use cases whose categories reflect the value-creating action in a concrete AI use case rather than the system's technical implementation, as summarized in Table 1. Two guiding questions structure this dimension:

- What output or result does the use of AI produce?
- What business purpose does it serve regarding value creation, such as reducing time or resource requirements, improving quality, supporting decisions, etc.?

Table 1: Value-creation profile

#	Category: Value-Creation Profile	Value-Creating Action
1	AI for Research, Communication & Design	Generates content (text, images, audio, video) for human consumption
2	AI for Software Development & Automation	Generates executable logic & systems that becomes operational infrastructure
3	AI for Insight Generation and Root-Cause Analysis	Explains relationships / causes, detects patterns
4	AI for Prediction, Decision Support & Optimization	Recommends actions and supports decisions
5	AI for Autonomous Actions & Processes	Executes actions independently (physically as a robot or virtually as a software agent)

The categories are not mutually exclusive: a single AI system may deliver several value contributions simultaneously. A predictive-maintenance system, for instance, may detect patterns or anomalies in noise levels, speed, or vibration that indicate a potential fault (category 3) and recommend corrective maintenance actions (category 4). Each use case is therefore characterized by its value-creation profile with the primary contribution highlighted where one dominates.

The value-creation profile is not intended to map directly onto technical distinctions such as generative or predictive AI. The same technical paradigm may support different value-creating actions, and the same value-creating action may be realized through different AI methods. For example, generative models underpin categories 1 and 2 (content and code generation) but increasingly also contribute to explanation (3) and to the reasoning of autonomous agents (5).

2.2.3 Cognitive demands: Blooms taxonomy of learning objectives

While the value chain locates an AI use case within organizational activity and the value-creation profile describes AI's contribution to the work process, neither dimension specifies the cognitive demands placed on workers. This perspective is essential for workforce upskilling, because similar AI use cases may require different levels of human competence depending on whether workers apply an AI tool, interpret its outputs, evaluate its reliability, or create new solutions with its support. A third dimension is therefore needed to capture the cognitive complexity of human work in relation to AI use.

AI-specific competence frameworks, such as UNESCO's AI Competency Framework for Students (UNESCO, 2024), provide important guidance on the knowledge, skills, and attitudes needed for responsible AI use. However, for workforce-oriented analysis, the relevant question is not which AI competencies learners should develop overall, but what cognitive demands workers face in specific AI-supported work processes. The revised Bloom's taxonomy provides an established framework for differentiating levels of cognitive complexity in learning and assessment. It distinguishes six levels, from lower-order to higher-order: remember, understand, apply, analyze, evaluate, and create (Anderson and Krathwohl, 2001; Krathwohl, 2002). At the foundational level, "remembering" involves retrieving relevant knowledge from long-term memory, while "understanding" focuses on determining the meaning of instructional messages. Higher levels, such as "evaluating" and "creating," require learners to make judgments based on criteria or reorganize elements into a new, coherent whole. Applied to organizational AI use cases, the Bloom-based dimension classifies the cognitive demand placed on

workers in AI-supported tasks. For example, generating a first draft with AI may require applying procedural knowledge, whereas assessing the reliability of an AI-generated recommendation may require evaluation based on domain knowledge, ethical reflection, and contextual understanding. Developing a new workflow with AI support may involve creative synthesis.

Recent literature has revisited Bloom's taxonomy in the context of digital and AI-supported learning environments. Gonsalves (2026) outlines how Bloom's taxonomy has been adapted in response to such environments, including AI literacy-oriented adaptations and approaches that emphasize critical engagement with AI-generated outputs. Ng et al. (2021), for example, map AI literacy onto Bloom-inspired levels, ranging from recalling and memorizing AI concepts to designing and developing AI applications. Farakish and Chae (2026) extend this discussion to generative AI, arguing that generative AI can support the production of outputs associated with higher-order cognitive tasks without necessarily ensuring the corresponding depth of human understanding, for example when students prompt essays without fully understanding the subject-specific concepts. These contributions confirm Bloom's relevance for distinguishing levels of cognitive engagement in AI-supported contexts. Here, it classifies workers' cognitive demands in concrete processes.

2.3 The AI Future-job-readiness and Reskilling Framework

Taken together, the three dimensions span a three-dimensional classification space in which each AI use case can be positioned according to *where* it creates value, *what* AI contributes, and *what cognitive demands* it implies. It can be visualized as a cube (Figure 1). Each use case occupies a position or a region within this space. The axes are conceptually independent, although particular combinations may recur empirically.

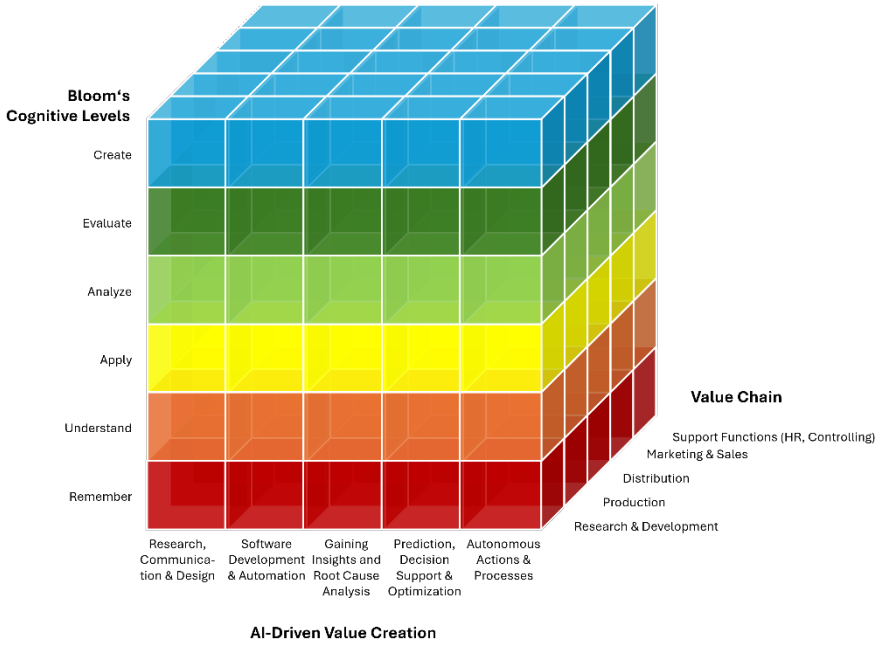

Figure 1: The AI Future-Job-Readiness & Reskilling Framework

The framework's analytical value lies in the interaction between its dimensions:

- **Value chain and value-creation profile.** Together, these dimensions show that the same AI value-creation, such as recommending actions, carries a different meaning when applied in different organizational contexts, while a single activity may involve several types of AI contribution.
- **Value chain and cognitive competencies.** Competencies are exercised within particular activities. Anchoring cognitive demands in the value chain therefore makes competency requirements addressable: it shows which competency is needed, by whom and in which organizational context.
- **Value-creation profile and cognitive competencies.** The way AI contributes to value shapes the cognitive work that remains with, or newly arises for workers. AI that generates content requires humans to critically evaluate and refine its output; AI that explains requires interpretation and contextualization; AI that recommends requires informed decision-making and accountability; and AI that acts autonomously requires supervision, governance, and the ability to intervene. This

relationship is mutual: the value-creation profile indicates which cognitive demands arise, while the competency perspective specifies the type and level of human capability required.

This triangulation allows us to move beyond broad lists of generic AI competencies and to derive targeted upskilling implications, thereby linking organizational AI use to future job readiness.

3. Methodology

This section describes the study design, data collection, sample, and data analysis used to apply the AI Future-Job-Readiness and Reskilling Framework to organizational AI use cases.

3.1 Study Design

To examine the analytical usefulness of the newly developed framework, a qualitative research design was adopted, using semi-structured in-depth interviews with managers as key informants. They described AI usage within their organization and the competencies their employees require (Taylor, Bogdan and DeVault, 2016, p. 104), situating organisational AI use in context and providing rich material for applying and refining the framework. The unit of empirical analysis is the organizational AI use case, defined as the use of one or more AI tools within a specific work process and for a specific organizational purpose. This allows to analyze AI as embedded in organizational activity rather than as an isolated technology. The study is guided by the following research question: How can the AI Future-Job-Readiness and Reskilling Framework be used to classify organizational AI use cases and derive workforce-relevant competency implications?

3.2 Data Collection

The interview guide was structured in four parts as depicted in Figure 2.

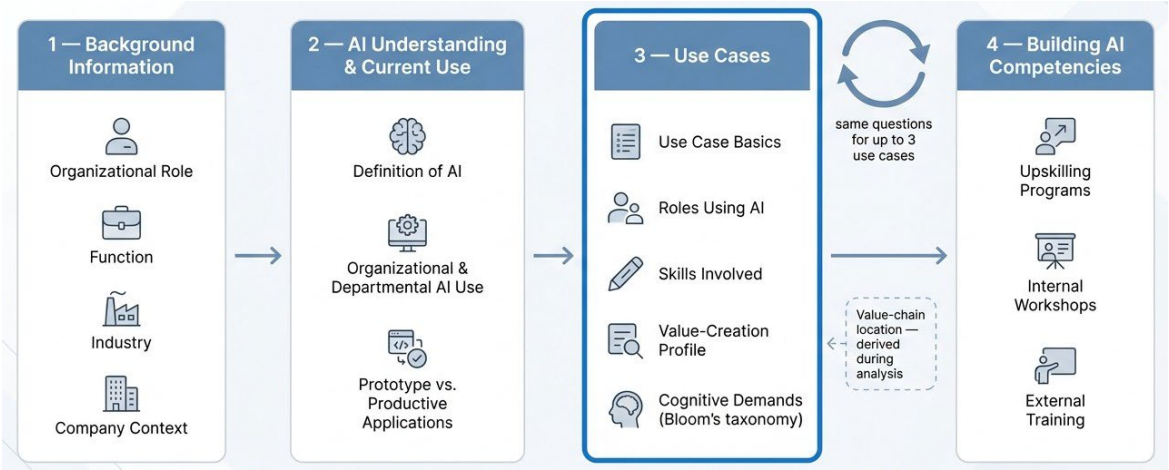

Figure 2: Interview Guide Structure

Fieldwork took place in March 2026. Interviews lasted 45 to 60 minutes, were conducted in German via Microsoft Teams, and were recorded with participants' consent. Recordings were transcribed using software-assisted transcription and manually corrected, including frequent misrecognitions of AI tool names, such as "cloud" instead of "Claude."

3.3 Sample and Recruitment

We conducted 14 semi-structured interviews with participants from 14 organizations in Germany. Participants were recruited through the authors' professional networks and via LinkedIn using a purposive sampling strategy designed to ensure variation across industries and organizational functions (e.g., HR, finance, IT, production, and R&D). Inclusion criteria targeted participants who (i) had direct experience with AI use in their work area and (ii) were in a position, typically as team or department lead, to reflect on implementation challenges, competency requirements, and training needs. We did not target participants whose organizations were only at an exploratory stage of AI adoption, as such interviews would provide limited insight into concrete AI use and related qualification needs. In two interviews, the primary participant invited a team member to join to add technical details. Data collection was concluded when the interviews had produced a sufficiently diverse set of AI use cases to assess the framework's analytical usefulness. Consistent with the concept of information power,

the aim was not to achieve saturation per se, but to obtain data that were sufficiently rich and varied to address the study objectives (Malterud, Siersma and Guassora, 2016). Table 2 presents the sample characteristics.

Table 2: Sample characteristics

No	Job Title	Gender	Industry experience (years)	Industry[1]
1	CEO	Female	22	Electricity, gas, steam and air conditioning supply
2	IT Coordinator	Male	15	Public administration and defence; compulsory social security
3	Head of Supply Chain Consultant; Senior AI Expert	Male Female	30 8	Manufacture of chemicals and chemical products
4	Deputy Head of Engineering & Repair; Building Department Clerk	Male Male	26 28	Real estate activities
5	Head of Revenue Management Analytics	Female	7.5	Travel agency, tour operator and other reservation service and related activities
6	Plant Manager Assistant	Male	10.5	Manufacture of motor vehicles, trailers and semi-trailers
7	Chief People Officer (HR)	Male	20	Education
8	Senior Sales Manager	Male	10	Retail Trade
9	Head of Installation Management; former Quality Assurance Team Lead	Male	6	Manufacture of other transport equipment
10	HR Business Partner for R&D	Male	18	Manufacture of machinery and equipment
11	IT Team Lead	Male	12	Manufacture of furniture
12	Head of IT and Digital Transformation	Male	40	Public administration and defence; compulsory social security
13	Agile Coach and Software Developer	Male	14	Computer programming, consultancy and related activities
14	Enterprise Architecture Manager for R&D	Male	25	Manufacture of motor vehicles, trailers and semi-trailers

3.4 Data Analysis

The transcribed interviews were first reviewed to identify discrete use cases. Coding was carried out manually using MAXQDA. Ambiguous cases were discussed within the research team until a consistent classification was reached. General statements about AI use, organizational readiness, or training practices were analyzed separately as contextual information. All identified use cases were coded along the predefined framework dimensions following a deductive coding strategy (Mayring, 2014). The resulting coding informed both the overall overview of AI use cases and the selection of two illustrative cases that are analyzed in depth in Section 4. The value-chain location was derived from participants' descriptions as described above. For the researcher coding, the value-creation profile was assigned by comparing participants' descriptions of the AI-generated output or result with the organizational purpose this output served. Similarly, the cognitive demand was assigned based on participants' descriptions of the AI-supported task, the workers' role in that task, and the competencies they considered necessary. Differences between participant reflections and research coding were documented and analyzed both as empirical findings and as input for refining the framework. In particular, they helped identify unclear category boundaries and cases where practitioner interpretations differed from the conceptual structure of the framework.

[1] Industry classification according to NACE Rev. 2.1, https://showvoc.op.europa.eu/#/datasets/ESTAT_Statistical_Classification_of_Economic_Activities_in_the_European_Community_Rev._2.1._%28NACE_2.1%29/data

4. Analysis of use Cases

The interviewees reported a remarkably diverse range of AI use cases. Across the 27 use cases, AI is applied both for everyday support tasks and for more advanced process automation. Figure 3 summarizes their thematic emphasis and groups them according to their dominant value-creation profiles.

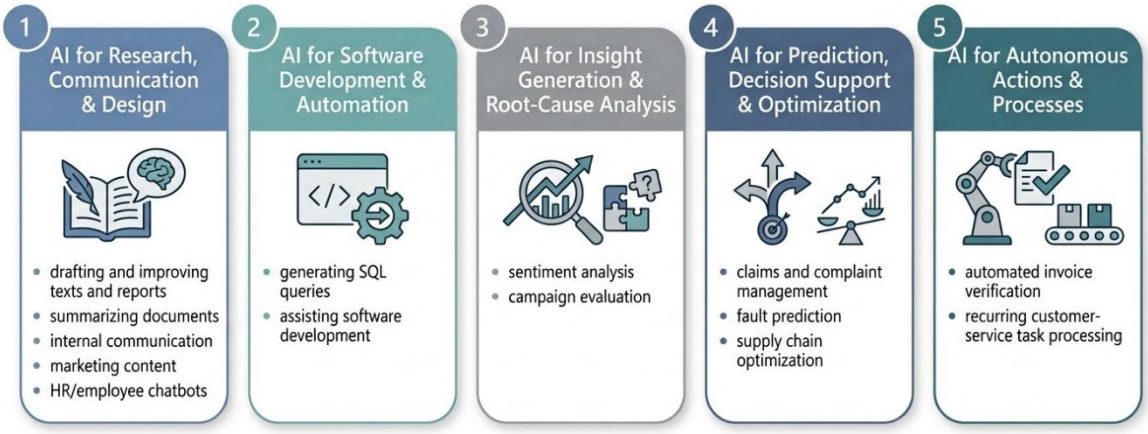

Figure 3: Value-creation profiles of the use cases

The following analysis demonstrates how the framework classifies two selected use cases before showing how this classification can be translated Into Workforce Competency Requirements.

4.1 Application Of The framework to Selected use Cases

The selected use cases are presented in Figure 1Figure 4 as compact profiles, summarizing each along the framework's three dimensions. The following remarks focus on the interpretive and methodological points that the figures cannot fully capture.

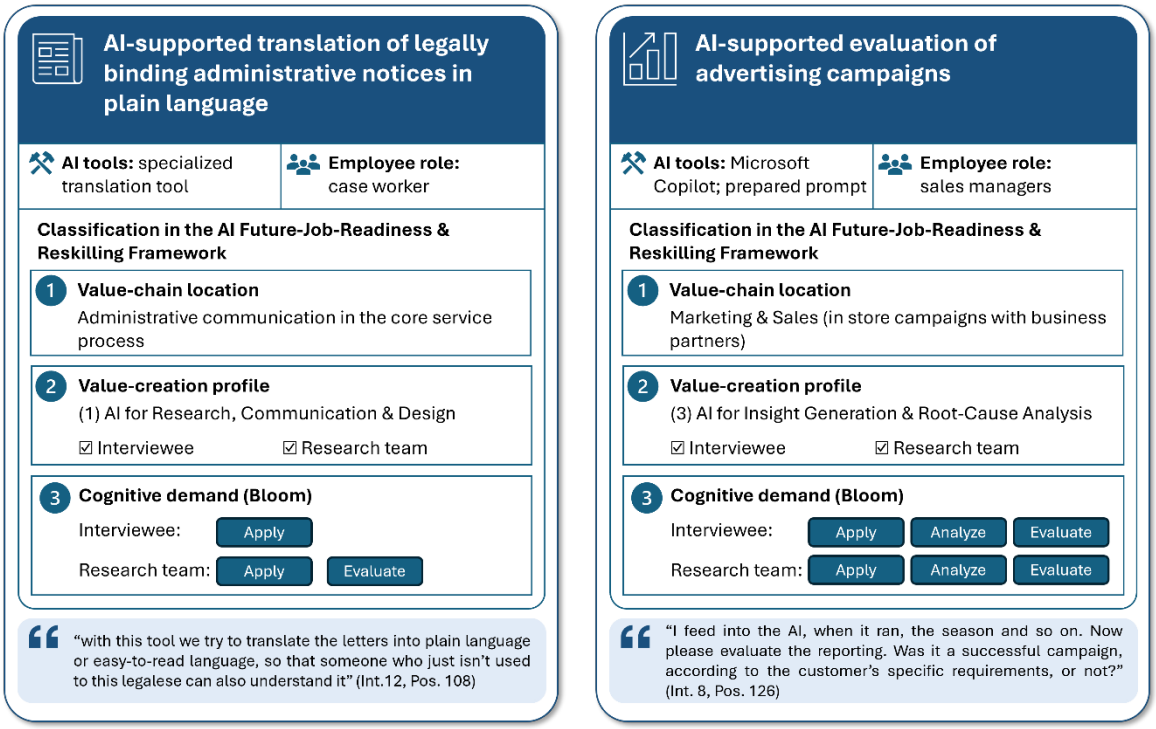

Figure 4: Profile cards

4.1.1 AI-supported translation of administrative notices into plain language (from interview 12)

Although the use case is profiled as "AI for Research, Communication & Design," the task is not merely linguistic: the generated plain-language version must preserve the original notice's legal meaning, scope, and implications. This distinction explains the divergence in the cognitive-demand coding shown in the figure. The interviewee

classified the work as *Apply*: "Ultimately, here again we are also at the stage of applying it. Well, they carry it out. They translate the text." (Int.12, pos.138), reflecting the operational use of the tool to produce a plain-language notice. The research team additionally coded *Evaluate* to account for the review-and-approval step, in which employees must judge whether the proposed text remains legally equivalent to the original. According to the interview partner, effective AI use in this case requires only basic AI literacy, particularly an understanding that AI-generated suggestions may be incorrect. However, it requires strong domain knowledge of the relevant legal framework, the individual case, and the sensitive personal, social, or health-related data involved, as well as communicative and ethical judgment regarding plain language for recipients with cognitive or psychological disabilities.

4.1.2 AI-supported evaluation of advertising campaigns (from interview 8)

This case illustrates that insight generation does not necessarily require a classical analytical AI system; here, it is supported by generative AI through a prepared, reusable prompt. For the sales managers using that prompt, the interview reflection and the researcher coding agreed on a cognitive demand of *Apply*, *Analyze*, and *Evaluate*. The interviewee reasoned their way to this range when reflecting on the task: "Applying, analysing, comparing, recognising structure. Yes, but you still have to interpret the result at the end, right? […] whether it really fits. You can't just take it as given. So, wait a minute, evaluate. I would even put it at the level of judging." (Int.8, pos.152). According to the interview partner, AI literacy requirements are limited because the task is structured through the prepared prompt. The main requirement is domain experience to assess AI-generated interpretations of campaign reports. The cognitive demands involved in developing the prompt were not assessed with Bloom's taxonomy in the interview because the questions focused on employees using AI. From the research team's perspective, prompt development falls under *Create*, as it involved designing a reusable AI-supported workflow that required both domain-specific knowledge and advanced AI-related competence, supported by iterative testing.

4.2 From Classification to Workforce Competencies

The two cases illustrate how the framework translates AI applications into competency requirements —shifting the focus from *whether* employees can use AI in general to *what* they must be able to do with AI outputs in a specific work process. Both cases identify evaluative judgment as the key competency requirement. This finding aligns with current AI literacy frameworks, which likewise emphasize critically assessing AI-generated outputs (UNESCO, 2024; OECD and European Union, 2026). Although AI reduces the effort required to generate or structure outputs, employees remain responsible for judging their correctness, plausibility, and contextual fit. This evaluation depends primarily on domain-specific knowledge: legal-administrative expertise in the first case and campaign-specific sales expertise in the second. Required AI knowledge, however, is limited; they need only know that AI outputs are provisional, without needing advanced technical AI expertise

A second implication concerns role differentiation. The retail advertising case shows that competency requirements may vary within one use case. Sales managers using the prepared prompt require limited AI literacy but substantial domain expertise, whereas developing a prompt additionally requires AI-related and workflow-design competence. This distinction matters for workforce planning because upskilling depends on employees' roles within the AI-supported process. Recent work also stresses that upskilling should be tailored to organizational learning systems and role requirements, rather than follow a uniform training approach (Appiah, 2025).

The analysis also shows that Bloom's taxonomy needs further specification when applied to AI-supported work. Higher-order cognitive demands may concern the AI system, the AI-generated output, or the appropriateness of AI use for the task. This distinction is important because evaluating an output mainly requires domain expertise, whereas evaluating AI use more broadly requires AI literacy and risk awareness.

5. Conclusion and Future Work

Preparing future-ready workers requires understanding how AI changes work. AI is introduced not only through new stand-alone systems but also as functionalities embedded in existing applications, often making its use and competency demands less visible. Competency requirements therefore arise from how AI is used in specific work tasks, what value it creates, and what responsibilities remain with employees. The framework presented here makes such uses locatable. From this perspective, future readiness depends less on employees knowing AI in general than on their ability to use AI functionalities productively and, where necessary, adapt them to their work tasks. In the discussed AI use cases, productivity gains arise when AI-related competencies are combined

with domain knowledge to make processes faster, less resource-intensive, or higher in quality. The findings should however be interpreted cautiously, as AI is evolving rapidly and current industry expectations may change as the technology matures.

By showing which Bloom-level cognitive demands arise, the framework supports educators and organizations decide what training should target, e.g., tool use, prompt adaptation, output evaluation, or workflow design. These differ in cognitive demand — evaluating AI output, for instance, requires higher-order analysis than routine tool use. Future-ready employees thus need both AI literacy and human-centered, domain-specific judgment.

This Bloom-level perspective also surfaces a tension relevant to higher education. Students may study to remember enough to pass, even when learning objectives target higher-order skills. In AI-supported work, however, knowledge becomes valuable when it can be applied, evaluated, and adapted to produce professionally usable outputs. The framework therefore implies that assessments should require application, evaluation, and design rather than recall.

Several directions follow from this work. The two use cases analyzed here served as a proof of concept for the framework's analytical logic. Yet, the study's specific context and sample may limit generalizability to other settings. A first priority is therefore to apply it to the remaining interview cases. This would reveal cross-case patterns, such as recurring Bloom levels and competency clusters, and provide a stronger basis for assessing the framework's reliability. A second step is to turn the competencies identified on the Bloom levels into concrete upskilling needs. Lower-order demands may require short procedural training, whereas higher-order demands require sustained development of domain-specific judgment. Mapping all use cases this way would support differentiated upskilling pathways.

Ethics Declaration: Ethical clearance was not required, as the study involved voluntary interviews with adult professionals about organizational AI use.

AI Declaration: AI tools (Copilot, ChatGPT-5, DeepL) supported language editing and clarity; Nano Banana supported figure design. All intellectual content, interpretation, and conclusions were developed by the authors, who reviewed and edited AI outputs for accuracy and appropriateness. AI tools (ChatGPT-5, PerplexityAI) also helped expand literature search terms, suggest keywords, and identify candidate publications; all searches were validated through academic databases, and all inclusion/exclusion decisions were made by the authors.

References

Aguado-García J-M, Alonso-Muñoz S, De-Pablos-Heredero C. (2026) 'The implementation of artificial intelligence in organizations by functional areas: A review and conceptual model', *Journal of Management & Organization*, 32(4):1119-1144. doi:10.1017/jmo.2026.10091

Anderson, L.W. and Krathwohl, D.R. (eds) (2001) '*A taxonomy for learning, teaching, and assessing: a revision of Bloom's taxonomy of educational objectives'*. Complete ed. New York: Longman.

Appiah, R.I. (2025) 'Corporate Strategies for Successful Workforce Upskilling and Reskilling in Response to AI Adoption - What Works, What Does not, and Why', *International Journal of Emerging Research in Engineering and Technology*, 6(1). Available at: https://doi.org/10.63282/3050-922X.IJERET-V6I1P112.

Chinoracky R, Stalmasekova N, Majercakova M, Neumannova R. (2026) 'Analysis of AI-Readiness of University Students Using AI-Competency Measurement Framework'. *Education Sciences*. 2026; 16(5):692. Available at: https://doi.org/10.3390/educsci16050692

Farakish, N. and Chae, H.S. (2026) 'Bloom's Taxonomy in the Generative AI Age', in D. Guralnick, M.E. Auer, and A. Poce (eds) *Creativity and New Technologies in Learning for the Workplace and Higher Education*. Cham: Springer Nature Switzerland (Lecture Notes in Networks and Systems), pp. 179–185. Available at: https://doi.org/10.1007/978-3-032-09905-1_15.

Gonsalves, C. (2026) 'Generative AI's Impact on Critical Thinking: Revisiting Bloom's Taxonomy', *Journal of Marketing Education*, 48(1), pp. 4–19. Available at: https://doi.org/10.1177/02734753241305980.

Krathwohl, D.R. (2002) 'A Revision of Bloom's Taxonomy: An Overview', *Theory Into Practice*, 41(4), pp. 212–218. Available at: https://doi.org/10.1207/s15430421tip4104_2.

Liu, X., Zhang, L., & Wei, X. (2025) 'Generative Artificial Intelligence Literacy: Scale Development and Its Effect on Job Performance' *Behavioral Sciences*, *15*(6), 811. Available at: https://doi.org/10.3390/bs15060811.

Long, D. and Magerko, B. (2020) 'What is AI Literacy? Competencies and Design Considerations', *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. New York, NY, USA: Association for Computing Machinery (CHI '20), pp. 1–16. Available at: https://doi.org/10.1145/3313831.3376727.

Malterud, K., Siersma, V.D. and Guassora, A.D. (2016) 'Sample Size in Qualitative Interview Studies: Guided by Information Power', *Qualitative Health Research*, 26(13), pp. 1753–1760. Available at: https://doi.org/10.1177/1049732315617444.

Mayring, P. (2014) *Qualitative content analysis: theoretical foundation, basic procedures and software solution*. Klagenfurt. Available at: https://nbn-resolving.org/urn:nbn:de:0168-ssoar-395173.

Murire, O. T. (2024) 'Artificial Intelligence and Its Role in Shaping Organizational Work Practices and Culture'. *Administrative Sciences*, 14(12), Available at: 316. https://doi.org/10.3390/admsci14120316.

Ng, D.T.K. *et al.* (2021) 'Conceptualizing AI literacy: An exploratory review', *Computers and Education: Artificial Intelligence*, 2, p. 100041. Available at: https://doi.org/10.1016/j.caeai.2021.100041.

OECD (2022) *OECD Framework for the Classification of AI systems*. OECD Digital Economy Papers 323. Available at: https://doi.org/10.1787/cb6d9eca-en.

OECD and European Union (2026) *Empowering Learners for the Age of AI: An AI Literacy Framework for Primary and Secondary Education*. Paris: OECD Publishing. Available at: https://doi.org/https://doi.org/10.1787/65cd27d4-en.

Schmid, T. *et al.* (2021) 'The AI Methods, Capabilities and Criticality Grid', *KI - Künstliche Intelligenz*, 35(3), pp. 425–440. Available at: https://doi.org/10.1007/s13218-021-00736-4.

Taylor, S.J., Bogdan, R. and DeVault, M.L. (2016) *Introduction to qualitative research methods: a guidebook and resource*. Fourth edition. Hoboken, New Jersey: John Wiley & Sons, Inc.

Teece, D.J. (2018) 'Business models and dynamic capabilities', *Long Range Planning*, 51(1), pp. 40–49. Available at: https://doi.org/10.1016/j.lrp.2017.06.007.

UNESCO (2024) *AI competency framework for students*. UNESCO. Available at: https://doi.org/10.54675/JKJB9835.

World Economic Forum (2025) *The Future of Jobs Report 2025*. World Economic Forum. Available at: https://www.weforum.org/publications/the-future-of-jobs-report-2025/.