

PAPER

Navigating AI Transformation: Human Resource Development Strategies for Corporate Learning

Sabine Seufert()
Judith Spirgi

University of St.Gallen (HSG),
St.Gallen, Switzerland

sabine.seufert@unisg.ch

ABSTRACT

Artificial Intelligence (AI) has revolutionised knowledge work through generative AI like ChatGPT, impacting coordination, creativity, and problem-solving. As AI adoption accelerates, understanding its implications for Human Resource Development (HRD) becomes crucial. This paper introduces a conceptual framework for HRD strategies in AI transformation, addressing the dearth of research in this area. Utilising a case study approach, we distinguish five strategies: Acceleration, Culture-driven Transformation, Data-Driven Agility, Personalized Learning, and Immersive, emotional Learning at the workplace. Each strategy caters to distinct organisational needs. Challenges include balancing rapid upskilling, managing cultural shifts, ensuring data quality, promoting self-directed learning, and implementing immersive technologies. The framework offers insights for organisations navigating AI-induced transformations in HRD practices. Further research and refinement are essential as AI technology evolves.

KEYWORDS

AI transformation, Human Resource Development, generative AI

1 INTRODUCTION

Artificial Intelligence (AI) has become a pivotal resource for knowledge workers, significantly transforming how information is processed, decisions are made, and complex problems are solved in the modern workplace [1]. The developments in the field of generative AI (such as ChatGPT) are accelerating the transformation of knowledge work. Generative AI can be defined according to [2, p. 2] “as a technology that (i) leverages deep learning models to (ii) generate human-like content (e.g., images, words) in response to (iii) complex and varied prompts (e.g., languages, instructions, questions)”.

For many aspects of knowledge work (e.g., coordination with others, creativity, problem-solving, language understanding and production), AI is expected to reach a similar performance level much earlier than was assumed five or six years ago [3].

Seufert, S., Spirgi, J. (2024). Navigating AI Transformation: Human Resource Development Strategies for Corporate Learning. *International Journal of Advanced Corporate Learning (iJAC)*, 17(4), pp. 80–93. <https://doi.org/10.3991/ijac.v17i4.47443>

Article submitted 2023-12-18. Revision uploaded 2024-03-18. Final acceptance 2024-04-01.

© 2024 by the authors of this article. Published under CC-BY.

Applications based on generative AI with their ability to generate content are expected to increase productivity, performance, and creativity in many activities [4, p. 12]. An MIT study has shown that the use of systems with generative AI can significantly reduce the total amount of time needed to create texts. This is especially true for idea generation and writing the first draft. However, the time required for editing increases. Moreover, the quality of work results improves [5]. A recent Harvard study analysing the impact of AI on the productivity and quality of knowledge workers comes to similar conclusions [6].

However, the potential benefits of generative AI vary across different business functions [3]. Sales, marketing, software engineering, customer operations and product development seem to be the areas that could benefit the most. In contrast, only limited potential is seen for HR, talent and organisational development. Nevertheless, successfully utilising generative AI is crucial in HR [3]. Employees in more operational roles, such as paralegals or marketing specialists, can use generative AI to create initial drafts, allowing them to spend more time refining content and identifying new solutions. Programmers can focus on improving code quality within tight deadlines and adhering to security requirements [4].

These changes illustrate how significant the need for development has become in many functional and task areas in the era of generative AI. It might be that employees often do not inform their superiors that they use ChatGPT. A survey conducted in March 2023 by the professional networking app Fishbowl (responses from more than 11,700 employees through the Fishbowl app) found that 43% of working individuals have used AI tools, such as OpenAI's ChatGPT, to complete tasks at work [7]. Of these individuals, 68% have not informed their superiors that they use these tools for work [7]. On the one hand, many companies face the challenge of navigating AI transformation. On the other hand, while employees are utilising AI tools, they are apprehensive about potential negative consequences. This situation underscores that promoting the competent use of AI tools is only one aspect; it is equally essential to identify development paths for employees that align with the corporate strategy for AI transformation.

As the adoption and utilisation of AI in companies and organisations gains momentum [3], Human Resource Development (HRD) must formulate strategies for employee skill development that align with the company's AI transformation. Due to the novel phenomenon of generative AI, we have not yet developed conceptual frameworks in research that could serve as guidance for HRD. This paper addresses this gap in research with the leading question: *How can HRD navigate AI transformation by pursuing a strategy aligned with the corporate strategy?*

The main contribution of this research is to propose a conceptual framework that distinguishes various HRD strategies for navigating AI transformation. This framework introduces and discusses a typology of these strategies, categorising them based on their characteristics and applications in different organisational contexts. Initially, we will outline the required competencies for AI transformation as underlying knowledge of HRD strategies. The main research method of our case study analysis is detailed in Chapter 3, followed by Chapter 4, which describes the typology and various strategies. Chapter 5 then discusses and concludes with the main insights.

2 REQUIRED COMPETENCES ALONG THE AI VALUE CHAIN

Despite the widely emphasised urgency of up- and reskilling in AI, little is known about the competencies employees need to successfully use AI [8]. The concept of

the AI value chain and the associated roles and responsibilities (see Figure 1) helps identify and develop the necessary competencies for dealing with (generative) AI [9]:

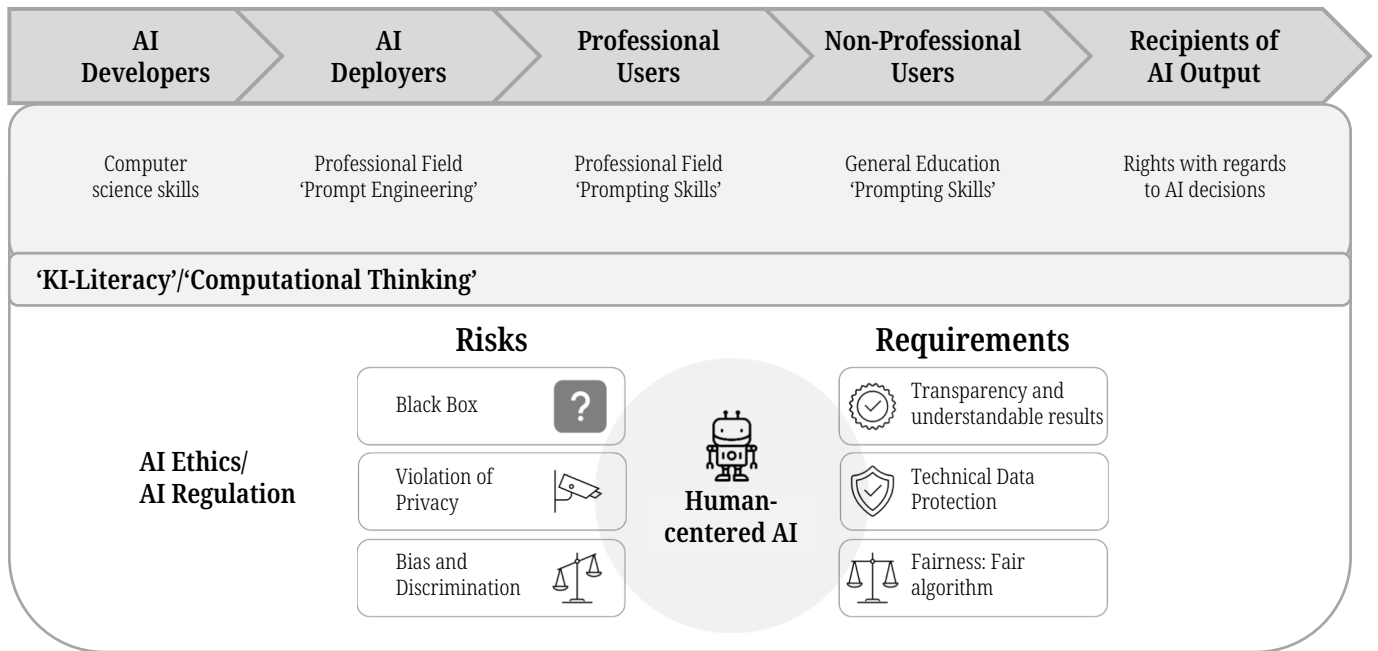


Fig. 1. AI Competencies along the AI value chain

AI developers are at the beginning of the value chain [9]. They create and train large language models or Foundation Models [10], such as GPT-x by OpenAI or LLaMA by Meta. They need specific computer science competencies, particularly in the field of Natural Language Processing. Other applications can then use these pre-trained language models via interfaces (API, Application Programming Interface).

AI service deployer realises their applications through API access to suitable language models [9]. They adapt these models for specific professional use cases by 'finetuning' (adjusting parameter weighting and special instructions as of 'prompt engineering'), thus creating specific web services. Finetuning often could involve rule-based approaches, such as dialogue controls and access to documents, leading to the development of hybrid architectures that combine the advantages of both worlds [11].

Professional users in companies, organisations, authorities, and institutions use AI applications for business tasks [9]. The development towards a professional use of generative AI service leads to the co-creating of digital products with the respective assistance systems.

Non-professional users utilise generative AI applications and use the products generated (texts, images, code, music) for personal purposes according to consumer rights [9].

Recipients of AI artefacts and decisions use the co-created and provided artefacts (text, graphics, code, music). These recipients can be individuals/ consumers, but they can also be companies, organisations, or authorities [9]. Recipients are at the receiving end of the value chain and, therefore, passive. Thus, two aspects of AI literacy are essential for recipients. First, they must be generally aware of the limitations that can apply to results from generative AI (e.g., potential data distortions). Second, they should be aware of their own rights (see DigComp Framework 2.2) [12]. For example, they are willing and able to object to a purely machine-made decision if it could significantly impact their own life and career (see DigComp Framework 2.2) [12].

AI literacy is an essential problem-solving skill for all participants in the AI value chain [13], [14], [15]. 'AI literacy' encompasses competencies such as critically evaluating AI, effectively interacting with AI, and using AI as a tool [16, p. 2]. Raising awareness of AI literacy and the rights of AI recipients is crucial for introducing AI responsibly, especially in the case of generative AI. It is important to note that programming skills are not necessarily a prerequisite for developing AI skills [17]. Most employees do not need to know how to develop AI applications. However, they should understand the basic principles and be able to use AI responsibly [18]. Furthermore, HRD must ensure that the professional use of AI in companies adheres to AI ethics, thereby preventing risks and complying with new requirements in line with AI regulations.

3 METHOD OF CASE ANALYSIS

This study uses case study analysis with a comparative approach to distinguish HRD strategies for navigating AI transformation. A case study approach is particularly effective in exploratory research for generating novel insights in areas where little is known about the phenomenon under investigation [19], [20]. This is the case as AI in HRD is a new research field [21]. A comparative research approach in HRD research can focus on an organisation's specific practices and systems. This approach can help identify similarities and differences in how HRD works and the phenomena it produces, thus distinguishing HRD strategies for navigating AI transformation [22]. In this research study, case selection is conducted based on the principle of theoretical sampling [23, p. 238]. Therefore, the samples are chosen not for their representativeness but for how they can help explore and expand upon various dimensions of a conceptual framework to differentiate common HRD strategies. To achieve this goal, we selected multiple companies, varying in size, industry, and learning culture, to provide a comprehensive view of how each strategy performs in different contexts.

All cases had to meet four specified selection criteria. These criteria were carefully defined to guarantee relevance and depth in the subsequent analysis. First, the companies must possess a clearly articulated mission for digital transformation. This ensures that organisations actively integrate digital technology into their business processes. Second, within these companies, the HRD department should have formulated and implemented a distinct strategy that aligns with the broader digital transformation goals. This alignment is crucial for examining the intersection of HRD with digital initiatives. Thirdly, the case company required a workforce exceeding 250 employees. Larger companies typically possess more expansive HRD departments and exhibit heightened professionalisation in HRD [24]. Finally, the chosen companies should have at least one year of experience in applying their HRD strategies within the context of digital transformation (high experience level of the phenomena under study) [25]. This duration is essential to ensure sufficient data and insights to assess the impact and effectiveness of the strategies in practice.

Data is gathered through document analysis. The documents were collected from various sources, including annual reports, edited volumes, company websites, and keynote speeches. Each case is examined in detail to understand the unique dynamics at play, followed by a rigorous comparative analysis across all cases. This comparative dimension is crucial for identifying common patterns, differences, and contextual factors influencing the success of each strategy [22]. This method aims to deepen our understanding of the interplay between different corporate learning

environments and the applied strategies, ultimately refining our typology of effective HRD practices in the corporate sector.

As a final step of our research, we pursued a communicative validation of our framework. We presented our research findings to the involved practitioners and researchers at the EURAM conference in 2022 [26] for their feedback, ensuring that our interpretations align with their experiences and perspectives. This iterative process enhances the credibility of our framework and allows for necessary refinements based on the insights and perspectives of practitioners and researchers.

4 RESULTS: CONCEPTUAL FRAMEWORK “HRD STRATEGIES TO NAVIGATE AI TRANSFORMATION”

In analysing our cases, we discovered that they can be differentiated in terms of goals (skills, competencies: generic vs. AI-focused) and approaches, indicating the use of AI for navigating the AI transformation. Based on Corea’s AI knowledge map [27], we distinguished three approaches for competence development: 1) Innovative approaches to competence development without AI, 2) approaches based on or supported by AI, and 3) approaches with AI-based embodied intelligence to enhance learning experiences. Embodied intelligence enables the integration of AI into both physical and virtual environments, empowering machines to interact intelligently with their surroundings [28], [29]. The following Figure 2 presents the conceptual framework of HRD strategies, distinguishing the five strategies.

Skills/Competencies	AI Focus	1 Acceleration strategy, ‘Fast upskilling’ for the entire company e.g., bootcamps, <i>Volkswagen, Levi Strauss</i>	3 Data-driven strategy for agile managing and developing skills, ‘SkillsTech’ <i>Swisscom</i>	5 Transformation strategy for immersive, emotional learning a) with extended Reality, e.g., AR, VR, & XR <i>Trumpf, Airbus</i>
	Generic	2 Culture-driven transformation strategy, change management, <i>Post</i>	4 Transformation strategy for self-organisation, personalised learning, <i>Infineon</i>	b) with emotion AI for soft skills e.g., AI-based Coaching <i>Facebook, Infosys</i>
		Without AI	AI-based solutions & learning analytics	AI-based embodied intelligence
		Use of AI		

Fig. 2. Typology for HRD strategies to navigate AI transformation

4.1 Acceleration/fast upskilling strategy

The ‘Acceleration Strategy’ aims to rapidly develop new competencies in employees, explicitly focusing on fostering widespread AI literacy within the company. A notable feature involves targeted training programs, facilitating the

swift acquisition of programming skills. These programs often employ innovative and collaborative methods to support companies' transformative initiatives. This strategy proves particularly pertinent for firms undergoing extensive transformation processes, aligning with corporate strategies seeking heightened flexibility and adaptability. Examples from the automotive industry and retail, namely Volkswagen Passenger Cars (VW) and Levi Strauss & Co., illustrate the effectiveness of this approach.

Volkswagen Passenger Cars (VW) is a brand of the Volkswagen Group and employs 182,860 people [30]. As part of the transition from an automobile manufacturer to an automobile and software company, VW has a high demand for further training of its employees. To meet this demand, VW follows a step-by-step approach encompassing four competency levels: Awareness, Beginner, Advanced, and Expert. The Awareness level (and partially the Beginner level) targets a broad audience and aims to raise awareness of AI. The Expert level is aimed at prospective Data Scientists. Participation in the courses for Advanced and Experts requires prior knowledge of programming with Python. In addition to in-house training courses, an external program, '42 Wolfsburg', and an internal program, 'Faculty 73', offer further training in software engineering. These two programs can be the first step towards more advanced AI training, enabling the transition from the awareness and beginner level to a higher level of competency [31].

A similar case is Levi Strauss & Co., an American clothing company that employs 14,800 people worldwide and is known for its Levi's brand denim jeans [32]. Due to the high demand for AI and machine learning expertise, Levi Strauss recognised the importance of developing talent from within its own ranks [33]. Therefore, in 2021, the company launched a boot camp for AI and machine learning for 43 employees from various departments, areas, and positions worldwide [34]. Levi's structured the Bootcamp as an eight-week virtual course, during which employees receive their regular salary and participate in 10-hour days with lectures, team exercises, individual work, homework, and office hours. The boot camp aimed to promote more flexible thinking and improve the company's use of technologies and data [33], [34]. The first AI Bootcamp cohort of 43 employees completed the program in 2021; the second cohort included 60 employees [35].

4.2 Culture-driven transformation strategy

A culture-driven transformation strategy aims to drive the company's cultural change to make the organisation fit for the future. Such a strategy focuses on future-relevant competencies and not just purely technological ones. This approach can be particularly relevant for regionally orientated or public companies. Such a strategy can be initiated top-down or bottom-up.

A typical case of this strategy could be Swiss Post. The Swiss Post has been an independent public institution since 1998 and enjoys a certain degree of entrepreneurial freedom. Culture is at the centre of Swiss Post's transformation strategy. Derived from a target culture model, Swiss Post identifies key future competencies, termed 'future skills'. These skills include innovative capability, customer focus, personal responsibility, and digital expertise [36]. These future skills guide systematic HRD practice at various organisational levels, influencing employee selection, onboarding, training programs, talent management, and career counselling. Swiss Post uses both top-down and bottom-up approaches to identify future skills. In a bottom-up approach, identifying skills required for various positions in the future involves employing methods such as 'Skill Canvas,'

‘Job Vision Lab,’ and data-driven market analyses. This dual approach integrates culture transformation with a data-driven strategy for skills development in technical fields, establishing a comprehensive foundation for successful and sustainable transformation [36], [37]. This means the company combines the culture transformation strategy with the following strategy: a data-driven strategy for skills development in technical fields.

4.3 Data-driven strategy for skills development

A data-driven strategy for agile skills development makes targeted use of data to promote agility in skills development. The main goal is to manage skills through an agile bottom-up approach, augmented by AI-powered solutions for skills management (SkillsTech). This approach is well-suited for data-savvy companies, facilitating efficient adaptation of competencies and swift responses to changes. The case of Swisscom and Novartis illustrates the implementation of such a skills strategy.

Swisscom AG, a Swiss telecommunications and IT company with 19,000 employees [38], actively seeks to enhance the qualifications and employability of its employees through targeted upskilling and reskilling [39]. Swisscom relies on Degreed as its Learning Experience Platform (LXP) to achieve this goal. This ‘SKILLup’ platform is a central tool for identifying and closing skills gaps and promotes a proactive learning culture within the company [40]. Additionally, SKILLup provides access to knowledge resources from external partners like LinkedIn, Pluralsight, Coursera, and internal sources. The platform emphasises targeted skills development, allowing employees control over their individual progress with personalised AI-recommended content [36], [39].

Novartis, a pharmaceutical and healthcare company, employs around 11,300 people in Switzerland [41]. In 2022, Novartis tested several modules of the Edcast SkillsDNA™ platform, including Skills Engine™, Skills Graph and Skills Studio, with 10,000 employees. Edcast’s solution enables the use of Lightcast’s skills taxonomy based on AI-supported document analysis of labour market data. Based on this taxonomy, Edcast’s Skills Studio allows Novartis to maintain and expand specific skills to offer personalised learning and development opportunities and individual career paths. Novartis prioritises social learning, user-generated content, and knowledge management, all supported by the Edcast Talent Experience platform. Therefore, the platform enables team members and managers to create and share easy-to-understand learning materials. The linked resources can be used specifically for development activities [42].

4.4 Transformation strategy for personalised learning

The transformation strategy of personalised learning and self-organisation focuses on employees’ needs-based, location-independent and self-directed learning. AI-supported learning environments that enable personalised learning, such as LinkedIn Learning, are used to make this possible. The strategy is particularly suitable for knowledge-intensive sectors such as insurance, technology, consulting and the financial industry. This strategy enables individualised learning, strengthens personal responsibility and promotes flexible learning approaches to prepare employees for complex requirements. A case study for the implementation of this strategy is Infineon.

Infineon is a semiconductor manufacturer based in Germany and employs 56,200 people [43]. In 2019, Infineon introduced the LinkedIn Learning platform to supplement its in-person and virtual training [44]. LinkedIn Learning is an online learning platform that teaches business, technological and creative skills in short video [45]. Infineon wanted this learning platform to enable needs-based, location-independent and practical learning. LinkedIn Learning's recommendation engine uses machine learning algorithms to generate relevant and personalised course recommendations for each learner [46], [47]. Infineon employees learn in courses and learning paths that they choose themselves or that are suggested by algorithms to help them understand technical topics or questions from their everyday work. LinkedIn Learning's recommendation algorithm is based on the individual employee's skills and previously viewed learning content. This allows learning content to be personalised and curated using AI approaches [44].

4.5 Transformation strategy for immersive, emotional learning

A further transformation strategy utilises embodied intelligence by incorporating AI into physical or virtual environments to enhance learning experiences. There are two distinct approaches to innovation strategies. The first approach involves integrating learning directly into the workplace (immersive learning) through virtual reality (VR), augmented reality (AR), and mixed realities (MR). The second approach is to use AI-powered learning solutions, such as AI chatbots, to simulate conversational situations and provide personalised feedback authentically.

The first method uses AI to create authentic and realistic learning environments that optimally prepare employees for demanding tasks while promoting safety and productivity in the workplace. Therefore, this strategy suits companies requiring training in areas such as safety, emergencies, production, logistics, machinery, equipment and health and safety. A case study for this skills development strategy is Trumpf.

Trumpf, a German mechanical engineering company with 16,554 employees (as of 2022) [48], has recognised the importance of VR for the future of learning. Trumpf uses a virtual learning environment featuring a digital twin of the 3D metal printer 'TruPrint 3000' to optimise training service technicians, operators and maintenance staff. Trumpf designs its learning environment based on the company's training centre. Moreover, it has the potential for individual learning and collaborative training using a VR head-mounted display (HMD) or semi-immersive setups with a laptop. This method significantly increases the effectiveness of employee and customer training, as it enables interactive and realistic training [49], [50].

A case study for the second approach of this strategy is LeaderAmp. LeaderAmp is an American company that works with CoachNet (American coach trainer) [51]. According to LeaderAmp, its clients include Facebook, Dropbox, and Infosys [51]. LeaderAmp introduces an AI-based solution for augmented coaching. It integrates rule-based and machine learning algorithms to achieve a more precise, less risky, and scalable coaching experience [52]. In a corporate setting, the solution should complement the role of a coach guiding individuals. The key functionalities of LeaderAmp include Adaptive Assessment, Journaling with EmotionMetric AI, eCoaching, Time Trial, Nurture Notes, and Instant AI Persuasion Coach. The last feature will be able to simulate conversational situations and provide feedback on the learners' formulations. In addition, LeaderAmp's solution uses dashboards for coaches and HRD departments to track and manage the impact of coaching assignments and minimise risks [52].

5 SUMMARY AND CONCLUSION

Advances in generative AI require a new approach to personnel and skills development. On the one hand, the increasing use of generative AI applications in the workplace makes it necessary to develop the skills of employees further (AI as a subject of competence development). Therefore, AI affects employees at all value chain stages, from AI developers to AI artefacts and decision recipients. On the other hand, applications based on generative AI present novel avenues for tailoring learning activities and materials to suit the unique requirements of employees (AI as a resource for competence development).

We developed a typology of five strategies that companies can pursue to promote corporate learning for navigating AI transformation. In the following, we summarise these strategies once again and conclude about possible patterns and the main challenges for each strategy:

Acceleration Strategy (Fast Upskilling). The Acceleration Strategy prioritises quick, intensive training, emphasising AI literacy for company-wide transformation, which is especially beneficial for firms undergoing strategic and operational shifts.

Application. Companies transitioning from traditional business models to software-centric ones, such as Retail and Automotive, may consider adopting this strategy.

Key challenges. Maintaining a balance between the rapid pace of skill acquisition and the effective assimilation of new knowledge might be critical. Quick learning may not necessarily result in long-term skills retention, notably when immediate implementation is lacking. Integrating rapidly acquired skills into existing job roles and workflows becomes challenging without a supportive workplace culture or infrastructure. Intensive training programs require substantial resources such as time, budget, and expert trainers, which poses challenges in resource allocation.

Culture-driven Transformation Strategy. This strategy aims to align the organisation's culture with future objectives and competencies, extending beyond purely technological skills. It underscores the significance of cultural alignment in skill development, ensuring sustainable and ingrained transformation within the organisational ethos.

Application. Organisations in the health sector, public enterprises, and companies providing public services can benefit from a culture-driven strategy. Such organisations often operate under strict regulatory frameworks. This approach promotes ethical practices and compliance with strict regulations, ensuring sustainable and socially responsible operations. Consequently, this approach ensures a balance between technological advancements and human-centric values.

Key challenges. Cultural transformation in established organisations may face resistance, necessitating effective change management and communication. Such cultural changes often involve various stakeholders with varying interests and perspectives. Aligning all these parties towards a common cultural goal can be challenging. Moreover, maintaining progress over time while dealing with various priorities and possible leadership changes can be challenging. Such transformations often require substantial resources regarding time, personnel, and finances. Resource allocation, particularly in sectors with tight budgets, poses inherent challenges.

Data-Driven Strategy for agile skills development. This Strategy relies on data for agility in skills development. It uses a bottom-up approach and AI-supported solutions (SkillsTech) to manage skills systematically. Companies can adapt to changes in skill requirements promptly, ensuring their workforce stays competent and competitive.

Application. It is particularly suitable for data-savvy companies that want to respond quickly to changing skills requirements and foster a culture of continuous learning and development. Given the fast-changing market, there is also a strong need for certain professional skills, such as digital and AI skills.

Key challenges: This strategy requires significant investment in technology and data analysis tools. Due to the novel approach, experiences are missing. Furthermore, there is a critical dependency on the quality and relevance of the data used. This strategy needs continuous updating to keep pace with evolving skill requirements. Additionally, the successful implementation needs to promote a culture of continuous learning and development.

Strategy for personalised Learning and Self-Organisation. The personalised learning and self-organisation transformation strategy prioritises individual learning needs and preferences. The strategy heavily relies on AI-supported learning environments, like LinkedIn Learning, to provide personalised learning experiences. These platforms adapt to the unique learning needs and styles of each employee. By enabling employees to choose their learning paths, the strategy promotes a sense of personal responsibility and self-organisation. Therefore, it allows the employees to concentrate on areas most pertinent to their roles and career aspirations.

Application. This strategy is especially effective in knowledge-intensive industries such as insurance, technology, consulting, and finance, where continuous learning and employee autonomy are valuable.

Key challenges. One primary challenge is ensuring employees remain engaged and motivated in a self-directed learning environment. Some individuals may struggle with maintaining discipline or motivation without the traditional structures of guided training. In addition, the effectiveness of this strategy depends on employees' digital literacy. Those less familiar with digital platforms may find navigating and utilising these learning resources challenging. Promoting self-directed learning needs a mindset change in managers and employees, which can take time and face resistance.

Strategy for Immersive Learning and Emotional Intelligence. This strategy uses VR, AR, and mixed reality to create immersive training environments mirroring real-world scenarios. These technologies enhance training effectiveness by facilitating authentic learning experiences. Additionally, AI-augmented learning solutions, such as AI chatbots, simulate conversational situations and offer personalised feedback.

Application. VR/AR/MR is highly effective in specialised industries where practical experience is crucial. It mainly benefits sectors involving complex machinery, safety protocols, and intricate procedures. Simulating real-life scenarios enhances skill levels and preparedness. Industry 5.0 pioneers adopt this approach as it aligns with their strategic goals.

Key challenges. Implementing advanced technologies like VR and AR necessitates substantial upfront investments in hardware, software, and the development of customised training programs. Employees may exhibit varying levels of comfort and proficiency with these technologies. Ensuring widespread adoption and effective use of VR and AR technology among all employees can be challenging. Creating and updating immersive content for VR and AR platforms is resource-intensive and requires ongoing commitment. Scaling these solutions across departments or locations while ensuring quality and consistency presents difficulties, particularly for larger organisations. Introducing new technologies often requires a cultural shift, potentially encountering resistance that effective change management strategies are crucial to address.

Our study has limitations. The limited representativeness of selected cases primarily centred on organisations in Germany and Switzerland due to practical access considerations. This geographical focus may restrict the generalizability of our findings to the broader industry or sector. Additionally, due to the specialised nature of strategies, our reliance on secondary data and abstained interviews could benefit from further triangulation for increased validity and reliability. Furthermore, AI is an evolving technology, incredibly generative AI (e.g., ChatGPT). Anticipating ongoing advancements, potential new strategies may emerge to address AI-induced transformations, necessitating further refinement of the framework.

The developed typology, including five main strategies, provides a comprehensive framework for organisations to understand how AI can be integrated into HRD practices. It offers a structured approach to analysing and selecting appropriate strategies based on specific organisational needs and contexts. This typology can spur further research in AI and HRD, providing a foundation for empirical studies that can test, refine, and expand upon the proposed strategies.

6 REFERENCES

- [1] T. H. Davenport and J. Kirby, “Just how smart are smart machines?” *MIT Sloan Management Review*, vol. 57, no. 3, pp. 21–25, 2016.
- [2] W. M. Lim, A. Gunasekara, J. L. Pallant, J. I. Pallant, and E. Pechenkina, “Generative AI and the future of education: Ragnarök or reformation? A paradoxical perspective from management educators,” *The International Journal of Management Education*, vol. 21, no. 2, p. 100790, 2023. <https://doi.org/10.1016/j.ijme.2023.100790>
- [3] M. Chui *et al.*, “Economic potential of generative AI: The next productivity frontier,” 2023. Accessed: Jul. 13, 2023. [Online]. Available: <https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/the-economic-potential-of-generative-ai-the-next-productivity-frontier#/>
- [4] F. Candelon, A. Gupta, L. Krayer, and L. Zhukov, “The CEO’s guide to the generative AI revolution,” *BCG Global*, 07 Mar., 2023. <https://www.bcg.com/publications/2023/ceo-guide-to-ai-revolution> [Accessed: Aug. 7, 2023].
- [5] S. Noy and W. Zhang, “Experimental evidence on the productivity effects of generative artificial intelligence,” *SSRN Journal*, 2023. <https://doi.org/10.2139/ssrn.4375283>
- [6] F. Dell’Acqua *et al.*, “Navigating the jagged technological frontier: Field experimental evidence of the effects of AI on knowledge worker productivity and quality,” *SSRN Journal*, 2023. <https://doi.org/10.2139/ssrn.4573321>
- [7] Fishbowl, “70% Of workers using ChatGPT at work are not telling their boss; Overall usage among professionals jumps to 43%,” *Fishbowl by Glassdoor*, 02 Feb., 2023. <https://www.fishbowlapp.com/insights/70-percent-of-workers-using-chatgpt-at-work-are-not-telling-their-boss/> [Accessed: Dec. 7, 2023].
- [8] S. Seufert, J. Guggemos, C. Meier, and K. H. Helfritz, “Trendstudie 2020: Auf dem Weg zur digital lernenden Organisation – Kompetenzen für die Personalentwicklung,” Universität St.Gallen (IWP-dBB, scil) / Deutsche Gesellschaft für Personalentwicklung, St.Gallen, 2020.
- [9] P. Hacker, A. Engel, and M. Mauer, “Regulating ChatGPT and other large generative AI Models,” in *Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency*, Chicago IL USA, 2023, pp. 1112–1123. <https://doi.org/10.1145/3593013.3594067>

- [10] R. Bommasani *et al.*, “On the opportunities and risks of foundation models,” 2021. [Online]. Available: <https://arxiv.org/pdf/2108.07258>
- [11] J. Wei *et al.*, “Finetuned language models are zero-shot learners,” 2021. [Online]. Available: <https://arxiv.org/pdf/2109.01652.pdf>
- [12] R. Vuorikari, S. Kluzer, and Y. Punie, “DigComp 2.2: The digital competence framework for citizens – With new examples of knowledge, skills and attitudes,” Publications Office of the European Union, 2022. <https://doi.org/10.2760/115376>
- [13] D. H. Autor, “Why are there still so many jobs? The history and future of workplace automation,” *Journal of Economic Perspectives*, vol. 29, no. 3, pp. 3–30, 2015. <https://doi.org/10.1257/jep.29.3.3>
- [14] S. Chuang and C. M. Graham, “Embracing the sobering reality of technological influences on jobs, employment and human resource development,” *EJTD*, vol. 42, nos. 7/8, pp. 400–416, 2018. <https://doi.org/10.1108/EJTD-03-2018-0030>
- [15] B. Trenerry *et al.*, “Preparing workplaces for digital transformation: An integrative review and framework of multi-level factors,” *Frontiers in Psychology*, vol. 12, p. 620766, 2021. <https://doi.org/10.3389/fpsyg.2021.620766>
- [16] D. Long and B. Magerko, “What is AI literacy? Competencies and design considerations,” in *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, Honolulu HI USA, 2020, pp. 1–16. <https://doi.org/10.1145/3313831.3376727>
- [17] S.-C. Kong, W. Man-Yin Cheung, and G. Zhang, “Evaluation of an artificial intelligence literacy course for university students with diverse study backgrounds,” *Computers and Education: Artificial Intelligence*, vol. 2, p. 100026, 2021. <https://doi.org/10.1016/j.caeai.2021.100026>
- [18] D. T. K. Ng, J. K. L. Leung, S. K. W. Chu, and M. S. Qiao, “Conceptualizing AI literacy: An exploratory review,” *Computers and Education: Artificial Intelligence*, vol. 2, p. 100041, 2021. <https://doi.org/10.1016/j.caeai.2021.100041>
- [19] R. K. Yin, *Case Study Research: Design and Methods*, 2nd ed. Thousand Oaks, Calif.: Sage Publ, 2009.
- [20] K. M. Eisenhardt, “Building theories from case study research,” *Academy of Management Review*, vol. 14, no. 4, pp. 532–550, 1989. <https://doi.org/10.5465/amr.1989.4308385>
- [21] J. Spirgi, “Analysing the AI transformation in HRD literature and practice,” in *Transforming Business for Good*, Trinity Business School, Dublin, Ireland, 2023, pp. 1–29.
- [22] G. G. Wang and J. Y. Sun, “Toward a framework for comparative HRD research,” *EJTD*, vol. 36, no. 8, pp. 791–808, 2012. <https://doi.org/10.1108/03090591211263521>
- [23] D. Silverman, *Doing Qualitative Research*: SAGE Publications Ltd, 2021. [Online]. Available: <https://www.torrossa.com/it/resources/an/5282195>
- [24] T. N. Garavan *et al.*, “L&D professionals in organisations: Much ambition, unfilled promise,” *EJTD*, vol. 44, no. 1, pp. 1–86, 2020. <https://doi.org/10.1108/EJTD-09-2019-0166>
- [25] A. M. Pettigrew, “Longitudinal field research on change: Theory and practice,” *Organization Science*, vol. 1, no. 3, pp. 267–292, 1990. <https://doi.org/10.1287/orsc.1.3.267>
- [26] S. Seufert and J. Spirgi, “Using AI education for managing the digital transformation in organisations,” Winterthur, 2022.
- [27] F. Corea, *AI Knowledge Map: How to Classify AI Technologies: A Sketch of a New AI Technology Landscape*. [Online]. Available: <https://francesco-ai.medium.com/ai-knowledge-map-how-to-classify-ai-technologies-6c073b969020> [Accessed: Jul. 24, 2022].
- [28] R. Pfeifer and F. Iida, “Embodied artificial intelligence: Trends and challenges,” in *Embodied Artificial Intelligence: International Seminar, Dagstuhl Castle, Germany, July 7–11, 2003; revised selected papers*, in Lecture Notes in Computer Science, vol. 3139, F. Iida, Ed., Berlin, Heidelberg: Springer, 2004, pp. 1–26. https://doi.org/10.1007/978-3-540-27833-7_1

- [29] A. Cangelosi, J. Bongard, M. H. Fischer, and S. Nolfi, “Embodied intelligence,” in *Springer Handbooks, Springer Handbook of Computational Intelligence: With 115 Tables*, J. Kacprzyk and W. Pedrycz, Eds., Berlin, Heidelberg: Springer, 2015, pp. 697–714. https://doi.org/10.1007/978-3-662-43505-2_37
- [30] Volkswagen Group, *Volkswagen | Brands & Models of the Volkswagen Group*. [Online]. Available: <https://www.volkswagenag.com/en/brands-and-models/volkswagen.html> [Accessed: Jan. 30, 2022].
- [31] J. Spirgi and A. Meier, “Case Volkswagen Passenger Cars – Upskilling strategy for employees,” in *Artificial Intelligence Education in the Context of Work*, D. Ifenthaler and S. Seufert, Eds., Cham: Springer International Publishing, 2022, pp. 199–214. https://doi.org/10.1007/978-3-031-14489-9_12
- [32] Levi Strauss & Co, *Company – Levi Strauss & Co*. [Online]. Available: <https://www.levistrauss.com/who-we-are/company/> [Accessed: Dec. 5, 2022].
- [33] G. Wu, *How Levi Strauss is Upskilling Its Workforce to Embrace Data and AI*. [Online]. Available: <https://venturebeat.com/ai/how-levi-strauss-is-upskilling-its-workforce-to-embrace-data-and-ai/> [Accessed: Nov. 26, 2022].
- [34] Levi Strauss & Co., *Employee Takeaways from Our Machine Learning Bootcamp – Levi Strauss & Co*. [Online]. Available: <https://www.levistrauss.com/2021/05/24/employee-takeaways-lsco-machine-learning-bootcamp/> [Accessed: Nov. 26, 2022].
- [35] M. McDowell, “Exclusive: Lessons from Levi’s data science bootcamp,” *Vogue Business*, 08 Nov., 2021. <https://www.voguebusiness.com/technology/exclusive-lessons-from-levis-data-science-bootcamp> [Accessed: Aug. 8, 2023].
- [36] C. Meier, “Skills-basierte Personalentwicklung mit Skills-Tech: 9. scil Trend- & Community Day 2022,” *Swiss Competence Center for Innovations in Learning*, 08 Sep., 2022. <https://www.scil.ch/2022/09/08/skills-basierte-personalentwicklung-mit-skills-tech-9-scil-trend-community-day-2022/> [Accessed: Aug. 17, 2023].
- [37] C. Rentsch and C. Erdin, “Kompetenzmanagement: Von der Strategie zur Kompetenzentwicklung,” St.Gallen, Sep. 1, 2022.
- [38] Swisscom AG, *Swisscom Startseite: Wir über uns | Swisscom*. [Online]. Available: <https://www.swisscom.ch/de/about.html> [Accessed: Dec. 3, 2022].
- [39] E. Stoffel, “Skillsmanagement -Herausforderungen und Ansätze rund um das Messen und Entwickeln der Skills-Readiness,” St.Gallen, Sep. 1, 2022.
- [40] C. Meier, *Kompetenz- bzw. Skills-basierte Personalentwicklung: Orientierung und Praxisberichte*. [Online]. Available: <https://www.scil.ch/2022/03/05/kompetenz-bzw-skills-basierte-personalentwicklung-orientierung-und-praxisberichte/> [Accessed: Dec. 3, 2022].
- [41] Novartis Schweiz, *Unsere Mitarbeitenden*. [Online]. Available: <https://www.novartis.com/ch-de/unser-unternehmen/unsere-mitarbeitenden> [Accessed: Aug. 18, 2023].
- [42] C. Meier, “Fokussierte Kompetenz- bzw. Skills-basierte Personalentwicklung mit Skills-Tech,” in *PersonalEntwickeln: Das aktuelle Nachschlagewerk für Praktiker*, S. Laske, A. Orthey, and M. Schmid, Eds., Neuwied: Dt. Wirtschaftsdienst, 2023, pp. 1–39. Accessed: <https://www.alexandria.unisg.ch/server/api/core/bitstreams/f77bc5ef-c49d-4782-95b7-be25076a90a2/content>.
- [43] Infineon Technologies AG, *About Infineon – Infineon Technologies*. [Online]. Available: <https://www.infineon.com/cms/en/about-infineon/> [Accessed: Jan. 19, 2022].
- [44] J. Spirgi and J. Tronsberg, “Using AI-Based linkedin video platform for personalised learning: The case at infineon technologies,” in *Artificial Intelligence Education in the Context of Work*, D. Ifenthaler and S. Seufert, Eds., Cham: Springer International Publishing, 2022, pp. 227–247. https://doi.org/10.1007/978-3-031-14489-9_14
- [45] LinkedIn Learning, *LinkedIn Learning – Übersicht | Learning Help*. [Online]. Available: <https://www.linkedin.com/help/learning/answer/73005> [Accessed: Nov. 16, 2021].

- [46] D. Agarwal, *An Introduction to AI at LinkedIn*. [Online]. Available: <https://engineering.linkedin.com/blog/2018/10/an-introduction-to-ai-at-linkedin> [Accessed: Nov. 8, 2021].
- [47] S. Chaudhari, M. Joshi, and G. Polatkan, *A Closer Look at the AI Behind Course Recommendations on LinkedIn Learning, Part 1*. [Online]. Available: <https://engineering.linkedin.com/blog/2020/course-recommendations-ai-part-one> [Accessed: Nov. 8, 2021].
- [48] TRUMPF, *Unternehmensprofil*. [Online]. Available: https://www.trumpf.com/de_CH/unternehmen/profil/ueber-uns/ [Accessed: Aug. 16, 2023].
- [49] TRUMPF, *Weiterbildung digital: TRUMPF setzt auf virtuelles Lernen*. [Online]. Available: https://www.trumpf.com/de_CH/newsroom/stories/weiterbildung-digital-trumpf-setzt-auf-virtuelles-lernen/ [Accessed: Aug. 16, 2023].
- [50] W. Taurel, *Ergebnisse des erfolgreichen Service-Forschungsprojekts „VASE – Virtual & Analysis Service im Maschinen- & Anlagenbau – Association for Service Management International*. [Online]. Available: https://www.afsmi.de/blog_artikel/einsatzerfahrung-von-vr-in-der-aus-und-weiterbildung.html [Accessed: Aug. 16, 2023].
- [51] LeaderAmp, *LeaderAmp*. [Online]. Available: <https://www.leaderamp.com/> [Accessed: Aug. 18, 2023].
- [52] N. Eggmann, “KI-basierte Systeme im Kontext von Corporate Learning,” Dissertation, Institut für Bildungsmanagement, Dissertation Universität St.Gallen, St.Gallen, 2022. Accessed: Aug. 18 2023. [Online]. Available: https://www.e-helvetica.nb.admin.ch/view/bel-2453599!urn%3Anbn%3Ach%3Aabel-2453599%3ADis5272.pdf?q=&v=all&urn=bel-2453599&waybackMode=page&start=0&rows=20&sort=score%20desc%2C%20ehs_urn_id%20asc

7 AUTHORS

Sabine Seufert is with the University of St.Gallen (HSG), St.Gallen, Switzerland (E-mail: sabine.seufert@unisg.ch).

Judith Spirgi is with the University of St.Gallen (HSG), St.Gallen, Switzerland.