

Towards Human-Centered Learning: AI-Supported Skill Management in a Large Automotive Organization

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Abstract: The use of AI in skill management has the potential to support personalized e-learning processes by identifying future skills, revealing skill gaps, and linking them to learning opportunities. At the same time, designing an AI-supported skill management system that is leveraging these potentials presents organizations with challenges. To investigate this design process, we conducted a qualitative case study based on 17 interviews and observations carried out during the pilot implementation of such a system. The case illustrates that AI-supported skill management does not automatically enable human-centered learning, but depends on balancing AI potentials, skill governance processes, and individual learning experiences. In this context, AI can be used to provide orientation in identifying future skills and deriving personalized learning impulses. This is accompanied by a reconfiguration of roles, responsibilities, and control, which are distributed across a shared sociotechnical governance structure.

Keywords: AI-Supported Skill Management, Sociotechnical Governance, Human-Centered Learning

1. Introduction

Digital transformation is reshaping today's work environment through increased speed, unpredictability, and technological advancement, resulting in rapidly changing qualification requirements within organizations. New skills emerge quickly, while existing skills lose relevance or become obsolete. This phenomenon, known as skill instability, confronts organizations with the challenge of identifying relevant skills and systematically developing them (Kusmin et al. 2024). One proposed response to address this challenge is the use of artificial intelligence (AI), which is expected to provide dynamic, data-driven, and personalized skill management solutions (Talodhikar and Farooqui 2025), thereby enabling tailored qualification measures (Freise et al. 2025).

Previous research has examined the potential of AI in workforce development and modern approaches to skill management, it remains unclear how the shift towards AI-supported skill management can be designed and what role humans will play in learning systems. Against this background, this study addresses the following research question: *How is AI-supported skill management configured during a pilot implementation in a large organization to support employee learning?* To explore this question, we conducted a qualitative case study within a large German automotive organization. The study is based on data collected through 17 interviews and observations carried out during the pilot implementation of an AI-supported skill management system.

The findings are structured along a sociotechnical perspective that considers the interplay between technological tools and platforms, organizational processes, and human-centered learning as an organizational phenomenon (Orlikowski 1992). The results demonstrate that AI-supported skill management does not automatically lead to human-centered learning. Instead, we describe the reconfiguration of a sociotechnical governance structure as a central aspect of this process by showing which technological infrastructure is required, how responsibilities should be redistributed and coordinated across actors, and under which conditions human-centered learning can emerge.

2. Theoretical Background

2.1 Skill Management in an Era of Skill Instability

The changing skill requirements for specific tasks and job profiles have long been regarded as a challenge for both business practice and academic research. In the past, the discussion was shaped by the concept of skills obsolescence. This term describes the depreciation of existing knowledge and thus the loss of the economic value of skills due to technological causes (de Grip and van Loo 2002). With the emergence of AI, both the dynamics of this process and the uncertainty surrounding skills have increased significantly (Meier and Seufert 2022). As a result, the focus of the discussion shifted toward the volatility and rapid transformation of skill requirements. Kusmin et al. (2024) move beyond the phenomenon of skills obsolescence and more

comprehensively describe this current skills instability as the continuous emergence, transformation, and obsolescence of skills caused by technological and labor-market-related changes.

As job requirements became increasingly dynamic, organizations' need for greater agility in describing and deploying their workforce also increased. At the same time, reskilling and upskilling became central measures for employee development. Consequently, organizational focus gradually shifted from traditional job-based approaches toward skill-based approaches (Collings and McMackin 2025). Modern skill management, which enables the design of a future-oriented learning ecosystem, is considered the foundation for structural workforce transformations (Darmawan 2025).

A key aspect of this development is that employees and their individual skills are placed at the center, rather than relying on rigid and hierarchically organized job descriptions (Collings and McMackin 2025). To make this manageable and transparent, systematic skill management is required, enabling the definition and description of required skills, their structuring, as well as their evaluation and validation (Meier and Seufert 2022). In this context, a skill management process should be implemented that is as dynamic and holistic as possible and that promotes the closing of individual skill gaps through skill development initiatives.

At the same time, aspects such as employees' motivation for lifelong learning, as well as organizational framework conditions such as learning culture and leadership, and the alignment of competencies with business goals, should be taken into account. Ultimately, skill management is intended to function as a navigator for the workforce through continuous technological change and to ensure that employees' individual needs are precisely aligned with market requirements so that emerging gaps can continuously be closed (Braun et al. 2025).

2.2 AI-Supported Skill Management as an Enabler for E-Learning

The use of learning technologies and AI for the analysis and management of skills is considered a core aspect of modern skill management (Braun et al. 2025). Data-driven models for individual skill profiles are intended to serve as a key factor in managing the complexity of skill requirements (Talodhikar and Farooqui 2025). Methods such as skills inference can be used to enable an up-to-date derivation and assessment of employees' implicit skills through the analysis of large-scale data streams, without requiring self- or external assessments. Furthermore, AI promises particularly detailed insights into employees' skill gaps, the quantification and analysis of skills, and the scaling of upskilling and reskilling measures (Tona et al. 2025). So-called SkillsTech solutions aim to integrate skill management and human resource development by, for example, using defined skill taxonomies as a reference point in digital learning experience systems. In this way, enablement of e-learning is created, as it allows a matching of employees' individual skill gaps with available learning content (Braun et al. 2025). According to Freise et al. (2025), AI can support the creation of personalized training plans that align with employees' individual career goals. Skill management is thereby closely linked to e-learning, as it reflects dynamic skill requirements and enables scalable, flexible, and personalized training.

2.3 A Sociotechnical Perspective on Human-Centered Learning

Despite the considerable potential of technological solutions, Meier and Seufert (2022) reveal a significant gap between the capabilities of modern SkillsTech solutions and their actual implementation. They further question whether AI is currently capable of supporting sustainable workforce transformation and employee development. Insufficient data availability, the complexity of human behavior, ethical concerns, as well as negative employee reactions, distrust, or lack of acceptance may represent inhibiting factors (Tambe et al. 2019).

From a sociotechnical perspective, organizational effectiveness is highest when social and technical systems interact harmoniously (Ang et al. 2025). In this context, learning is not understood solely as a technologically driven process, but rather as an active process of appropriation in which employees adapt technologies and integrate them into their work and learning practices (Orlikowski 1992).

To bridge the gap between technological possibilities and actual organizational value (Tian et al. 2023), increasing attention is being directed toward human-centeredness (Tona et al. 2025). In this approach, the individual needs of employees are placed at the center instead of offering standardized learning programs. In this way, employees are enabled to shape their own development more actively through self-determination, autonomy, and empowerment (Freise et al. 2025).

3. Methodology

Our case study examined a large automotive corporation based in Germany that, in response to a challenging business environment, aims to transform its workforce. The objective is to strengthen workforce adaptability through more suitable and future-oriented qualification. To achieve this, AI is intended to be used for process optimization. In line with this objective, the HR department developed an AI-supported skill management approach designed to make individual employee skill profiles visible and enable systematic gap analyses. The aim of the pilot project was therefore to examine how market-related skill requirements can be translated into an organizational skills taxonomy, how employees' existing skills can be made visible, and how the resulting skill gaps can be linked to targeted learning and development opportunities.

Guided by the objective of understanding the impact of AI on human learning in the context of organizational skill management, we conducted a qualitative case study (Yin 2018) to investigate that pilot implementation.

The data is based on a multi-perspective design and includes 17 semi-structured interviews (Mayring 2014), observational data from approximately 60 meetings (weekly and biweekly) carried out during a nine-month pilot phase as well as internal and external document material. The interviews were conducted between August 2024 and June 2025 and lasted between 33 and 60 minutes ($M = 51.26$ minutes). The semi-structured interview guide covered questions on continuous competency reassessment, including processes, tools, stakeholders, information sources, barriers, and enabling factors, as well as questions on current and future IT competencies and short-, medium-, and long-term approaches to competency development in the context of AI-supported skill management. This project-internal sample was well suited to the exploratory focus of the study, as the participants possessed detailed knowledge of the processes involved in the design and implementation of the pilot project. Reliance on interview data alone was reduced by triangulating the interview findings with observational data (Yin 2018).

Participants were selected based on their key roles within the pilot project, as they were directly involved in defining the skill infrastructure and integrating skill data into learning systems. These include HR digitalization specialists ($n = 5$, ID: T), stakeholders responsible for skill management in HR and IT ($n = 6$, ID: O), and learning experience designers ($n = 6$, ID: L) responsible for learning experience. All interviews were audio-recorded, transcribed, anonymized, and included in the analysis.

Data analysis was conducted using qualitative content analysis according to Mayring (2014). The aim was a systematic reduction of the material to identify central patterns of meaning. Significant text segments were coded and iteratively summarized into categories. The resulting codes were assigned to three overarching main categories, which were contextualized within sociotechnical theory (Orlikowski 1992) along the technological, organizational, and human-centered learning dimensions. The development of subcategories was deliberately omitted, as the main categories provided a sufficiently differentiated structure to address the research question. The analysis process was structurally supported using Word and Excel (Ose 2016).

4. Findings

4.1 Building an AI-Supported Skill Infrastructure

Our study identifies three core elements of the emerging skill infrastructure that appeared central in the pilot implementation of AI-supported skill management.

4.1.1 Development of an AI-Supported Skill Library

As a central infrastructural component of AI-supported skill management, the organization implemented an AI-generated skill library based on large-scale benchmark workforce data. It serves as the foundation for aggregating and standardizing skill data and includes AI-identified skills. It establishes the basis for the organization's internal skill taxonomy, which was integrated into existing Human Resource Management (HRM) and learning experience systems.

4.1.2 AI-Supported Skill Identification and Bundling

The described infrastructure is complemented by an intended enabling mechanism that not only identifies relevant skills, but also assigns synonyms to them and clusters them conceptually. This continuous process of pre-structuring and simplification makes skill data more precise and manageable. "AI is supposed to help us

identify the right skills and match them with the right trainings. AI is supposed to help us assign synonyms to skills and create bundles of skills. Another aspect is that we want to use AI to derive skills automatically.” (T2)

4.1.3 Integration of AI-Supported Skill Infrastructure into HRM and Learning Experience Platform (LXP):

The identified skill data were integrated into the core functionalities of existing HRM systems which serve as a single source of truth for the functional areas of skill management and learning. A key aspect was the integration of skill data into the organization’s LXP. “The skill catalog as such serves different functions within our large HRM system [...] for example in combination with our LXP platform.” (O6)

In this context, skill data support the platform’s recommendation mechanisms, as they are tagged to training content, thereby providing orientation in individual learning processes, in the assessment of one’s own skills and the identification and closing of skill gaps.

4.2 Distributed Skill Governance

In the pilot context, the availability of a new skill infrastructure appeared to redistribute aspects of skill management governance. Two central aspects of this process were the emergence of new roles and coordination between them. Our case study therefore illustrates how these distributed responsibilities were aligned in practice.

4.2.1 Distributed Roles and Responsibilities

Within this context, HR assumes responsibility for the central structuring of the skill taxonomy and for steering the operationalization of skill management. “We now have the data [...] This means that in the future we will manage much more centrally.” (O6) One of these steering functions consists of regularly updating the skill taxonomy through structured review cycles (three to four times per year), during which AI-generated skill data are validated by HR and integrated into existing HRM and learning systems. “We use review cycles for the job and skill catalog. We plan to perform updates three to four times a year.” (O3)

Line managers are responsible for applying the taxonomy and specifying the requirements of individual positions. In dialogue with employees, for example during annual performance reviews, they define relevant skills and required proficiency levels within the respective organizational context, enabling them to identify and document skill gaps.

Employees constitute an active part of this dialogue and independently complement their individual skill profiles as a basis for setting their personal learning goals and creating individual qualification pathways.

4.2.2 Coordinating AI-Supported Skill Management Across Organizational Actors

Distributed responsibilities are aligned in practice through a shared AI-supported skill infrastructure that underpins a multi-level skill governance approach. Within this process, coordination is achieved through recurring review cycles as a governance mechanism, the integration of the skill infrastructure into HRM and LXP systems as a technical mechanism, and continuous dialogue between HR, line managers, and employees as a social mechanism. The AI-supported skill infrastructure serves as a blueprint that constitutes a higher-level, organization-wide reference structure standardized and embedded within HR systems.

The organization aims to establish a bottom-up approach in which employees keep the system responsive to actual work practice. In this sense, employees are not treated as passive objects of skill assessment, but rather as active contributors shaping their own learning pathways. “We need to create a framework in which people can independently adapt their profiles according to the skills they actually need. We may sit next to each other in the same office with the same job description, yet you may still perform different tasks than I do and therefore require a different skill profile. This individualization is therefore extremely important. In this way, we can achieve this level of individualization, and every employee can also independently determine their own skills.” (O2)

4.3 Conditions for Human-Centered Learning

The pilot implementation revealed four conditions that appeared to shape whether AI-supported skill management could become human-centered in practice.

4.3.1 *Perceived Individual Value*

The findings suggest that in this pilot context, human-centered learning was closely linked to employees' willingness to participate in skill profiling and disclose skill data.

For this reason, HR actors emphasized the need to create visible incentives and recognizable individual benefits for maintaining one's own skill profile. These benefits may include improved training recommendations, broader career opportunities, or access to new projects. However, the pilot also indicates that such benefits are currently limited, as the skill-based logic has thus far mainly been integrated into the learning environment rather than into the broader HR architecture. Consequently, human-centeredness does not emerge automatically through personalization alone, but rather depends on whether employees perceive genuine value in engaging with the system. "We will have to establish processes in which employees realize that maintaining their skills actually benefits them, whether in terms of career development, better training recommendations, new career paths, or exciting project opportunities that are suggested to them. [...] A major challenge is gaining people's acceptance to disclose their data and enabling them to recognize a benefit in doing so." (O3).

4.3.2 *Dialogical skill Gap Analysis*

The findings suggest that employee development remains a socially negotiated process rather than a purely data-driven one. Employees articulate their goals and interests during performance and development reviews, in which skill gaps are jointly interpreted together with their line manager. "Exactly, whereby it is important to us that the employee remains in the driver's seat, within our group this is very important. Employees must clearly articulate what their goals are and what they want to achieve. The plan for the qualification pathway is then developed together." (O5) Skill assessments and development decisions are ultimately embedded in dialogue and cannot be fully delegated to the system. This indicates that human-centered learning in AI-supported skill management is characterized by a hybrid logic in which algorithmic recommendations and interpersonal sensemaking complement one another. "In the end, it will always remain with the manager and the employee to assess skills. This will always take place in a personal conversation. That is irreplaceable." (O3)

4.3.3 *Enablement for Skill Management Participation*

In the pilot context, human-centered learning in AI-supported environments appeared to require active enablement. HR and business units described it as their responsibility to support employees in using learning platforms and to develop the capabilities required for effective action in increasingly data-driven learning environments. This includes not only familiarity with the learning platform itself, but also broader data-related skills. "It is very important to empower people to engage with LXP platforms." (T5) As digital systems make learning needs, development opportunities, and skill gaps more visible, employees are increasingly expected to interpret information, operate digital tools, and make decisions based on data. Human-centered learning therefore also creates a new demand for digital and data literacy. "Everything is moving toward data usage and data-based decision-making. Through digitalization, many things become more transparent. At the same time, I have much more information and can analyze things more effectively and comprehensively. However, this also requires being capable of using tools, thinking in terms of data, and making data-based decisions [...]. In principle, every employee should become a small data scientist." (T3) The findings suggest that organizations need to actively support this transition through awareness-building and empowerment measures if AI-supported skill management is intended to empower rather than burden learners.

4.3.4 *Access to Personalized Learning Opportunities*

To address emerging qualification needs, HR uses individual skill profiles to offer data-driven, tailored, and future-oriented training opportunities. "Employees can formulate their own goals accordingly, and we then, of course, use this information to determine which training programs we need to provide." (O4) Employees can autonomously choose from options provided through the learning experience platform.

5. Discussion

5.1 Reconfiguring Sociotechnical Governance for Human-Centered Learning

Within the context of the AI-supported skill management approach, we identified a socio-cultural shift in skill-related responsibilities in our case study. Rather than remaining primarily embedded within HR, skill management appeared to become a sociotechnical structure involving HR actors, AI solutions, digital systems,

managers, and employees, thereby transforming who contributes to skill identification, how development needs are interpreted, and where responsibility for learning and employability is situated. Meier and Seufert (2022) highlight the associated need for coordination and collaboration. Our work builds on this by showing how the responsibility is configured in practice, and how core elements of the skill infrastructure, new roles, and coordination processes interact, as well as under which key conditions they can foster human-centered learning.

However, this reconfiguration of responsibility does not necessarily imply a loss of relevance for HR. Rather, the findings of our study indicate a transformation of the HR function from an administratively oriented role toward a more strategic and advisory one. In line with Darmawan (2025), our case study suggests that HR increasingly acts as an orchestrator of skill-related infrastructures. In this role, HR provides access to future-oriented skills, translates external skill demands into the internal skill taxonomy, and establishes conditions for systematic engagement with development needs.

However, its control is exercised less through the direct specification of development activities and more through the design of guiding frameworks, such as the skill taxonomy and digital platforms, which shape how skills become visible and actionable within the organization.

At the same time, our findings point to the importance of line managers as interpretative intermediaries within skill management. While AI-generated skill data provided by HR offers strategic orientation, it remains too abstract to be fully understood by all employees or to directly guide individual development in practice. Line managers contextualize this skill data by relating it to specific roles, tasks, and concrete job requirements. In doing so, they identify skill gaps and translate the abstract skill taxonomy into situated developmental priorities. This is consistent with the work of Braun et al. (2025), which emphasizes the importance of managerial involvement in skill development and skill gap closure. Our findings reinforce this perspective by showing that line managers also function as a critical interface between data-driven skill intelligence and the lived realities of employees' work practices.

Employees, in turn, emerge as active actors in the dialogue on skill requirements and as co-producers of skill visibility, rather than passive recipients of development measures. However, the findings also suggest that enhanced agency is accompanied by new forms of responsibility that need to be actively developed. It is already established that the effectiveness of skill management systems is particularly high when employees are willing to disclose their skills and engage with e-learning platforms (Tona et al. 2025). Responsibility for employability and development appeared to be partially shifted toward the individual.

While Tona et al. (2025) describe the pursuit of objectivity in employees' self-assessment of skills, our pilot study suggests that subjectivity in AI-supported skill management can be of particular value. Rather than being a problem to be eliminated, this individuality represents a valuable resource for human-centered learning, as it enables the interpretation of development needs in relation to actual work practices, personal goals, and social dialogue. In line with Braun et al. (2025), our study further shows that the value of this subjectivity lies not only in its relevance for employees, but also in its contribution to organizational learning, as interpersonal dialogue creates meaningful opportunities to interpret skill gaps and shape development pathways.

In summary, the case suggests that the pilot implementation of AI-supported skill management was associated with a decentralization of skill governance, in which HR was no longer solely responsible. On the one hand, relevant skills are increasingly made visible within the organization through AI, data infrastructures, and recommendation systems. On the other hand, interpretative and development-related decisions remain embedded in the dialogue and interaction between line managers and employees. Our study therefore illustrates a shift from centralized administrative skill management towards a more distributed form of sociotechnical governance, in which agency and control are not opposing forces but are continuously renegotiated between human and technological actors. In this context, AI-supported skill management should therefore not be understood as a replacement for human judgment, but as an enabler of more human-centered learning processes.

5.2 Implications, Limitations and Future Research

This study contributes to the theoretical debate on AI in skill management by illustrating, through a pilot case, that AI-supported skill management constitutes a complex and ambivalent field rather than a purely technological advancement. The findings are situated within the tension between technological enthusiasm and practical skepticism that characterizes the implementation of such systems in organizational contexts. By providing empirically grounded insights into the integration of AI-generated skills into organizational learning

platforms, the study illustrates how AI-supported skill management can serve as a foundation for learning recommendation mechanisms, while remaining dependent on the interplay between technological, organizational, and human actors.

The case illustrates that such systems have the potential to enhance personalized learning, while also emphasizing the importance of aligning future-oriented skills with organizational structures and human-centered learning practices. For practitioners, it is not sufficient to merely introduce the technology or define technical implementation conditions. Rather, AI-supported skill management must be designed in a way that actively enables the interplay between technological systems, organizational structures, and human actors.

Our contribution, while insightful, faces several limitations. (1) The sample size of 17 participants entails a risk of bias and limits the representation of diverse perspectives, the depth of insight, and the generalizability of the findings. (2) Generalizability is further constrained, as the study was conducted within a single organization. However, given the organization's global scale, the findings still provide insights into core aspects of implementing AI-supported skill management that may be relevant for other organizations. (3) The study does not directly capture employees' perspective in detail through interviews. Nevertheless, the selected sample provides a relevant overview, as participants were actively involved in shaping the process.

Future research could address these limitations in several ways. First, investigating the employee perspective in AI-supported skill management systems. In particular, it may be useful to distinguish between multiple forms of employee involvement, ranging from active co-creation of skill profiles and governance contributions to the use of system-generated learning recommendations. This dual role highlights employees both as active contributors to and users of AI-supported skill ecosystems. Second, longitudinal studies should be conducted to investigate the long-term effects of AI-supported skill management on employability and individual learning activities. In addition, the technological and organizational maturity of AI-supported skill management should be considered over a longer period of time. Finally, we believe that future research is needed to confirm our assumptions by examining other organizations in various industries and including further experiences and opinions through a larger number of interviews.

6. Conclusion

AI has the potential to modernize skill management in addressing skill instability, redefining humans' role in future learning and skill management systems. Our study suggests that leveraging this potential requires an understanding of the interplay between technological, organizational, and human factors. In this regard, we identify sociotechnical structures that appeared relevant for fostering human-centered learning in the pilot context. These prerequisites include the organizational and social embedding of AI, a clearly recognizable individual value for employees in disclosing and maintaining their skill profiles, the preservation of employee agency, targeted enablement for the use of digital learning environments, and the central role of personal dialogue in identifying and addressing skill gaps. Overall, the findings indicate a shift toward more human-centered learning approaches, in which organizations tailor learning opportunities based on individual competence profiles and development needs. In this context, AI does not replace human judgment but provides an orientation framework for e-learning.

Ethics Declaration

All interviews were anonymized, voluntary, and conducted with informed consent, and no sensitive personal data were collected. The study complies with ethical standards and data protection regulations.

The results, opinions and conclusions expressed in this study are not necessarily those of Volkswagen Aktiengesellschaft.

AI Declaration

The authors declare that they have used AI for proofreading and to enhance the readability of this manuscript. After using this service, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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