Skills in Flux – Challenges in AI-based Skills Management and Skills Profiles

Research Paper

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Abstract. The changing world of work, driven by automation and digital technologies, requires a workforce that continuously adapts its skills in order to be competitive and employable. This dynamic environment has fueled the demand for advanced skills management, with artificial intelligence (AI) playing a critical role in measuring and supporting individual skills development. This paper looks at AI-based competency profiles as a strategic tool for talent acquisition, retention, and development and highlights their potential challenges. Using semi-structured interviews with experts from HR, education, and industry, we explore the multiple challenges of AI-based skills management from a theoretical, conceptual, and practical perspective. Our findings reveal complex problems at the individual, team, organizational, and systemic levels that form a basis for the development of effective AI-based skills management strategies. This research highlights the importance of using AI to foster an adaptable and skilled workforce that meets both current needs and future challenges.

Keywords: Skills Management, Skills Profiles, Challenges, Expert Interviews

1 Introduction

The contemporary labor markets are in a constant state of flux due to a multitude of factors such as automation, artificial intelligence (AI), and the ongoing digital revolution that have sped up a reallocation of tasks in labor markets. These transformations necessitate continually adapting skills among the workforce to remain competitive and employable (Traumer et al., 2017). According to Bakhshi et al. (2017), there will be a shift in focus toward interpersonal, higher-order cognitive, and systems skills. With jobs being displaced or transformed by technology, a growing demand for re-&up-skilling arises. According to a World Economic Forum report, 50% of employees will need a reskilling by 2025 (World Economic Forum, 2023). As these numbers demonstrate, employers are confronted with the challenge of staffing positions with qualified individuals with the latest and most relevant job-related skills. Accordingly, there is a growing need for lifelong learning, where individuals receive personalized suggestions for continuing education (Ritz et al., 2023a). Nevertheless, AI may not only be one relevant driver of skills changes, but it could also contribute to being the solution, As it can address the demand for personalized skills management, which is a comprehensive approach to identifying, assessing, and cultivating the skills of the workforce.

The foundational premise of our inquiry is predicated upon conceptualizing a virtual representation of an individual's skill set and proficiency (Zhao et al., 2019a). In general, a skills profile, either physical or digital, encapsulates a comprehensive overview of a person's abilities, experiences, educational background, and training achievements (Freise and Hupe, 2023). The adoption of digital platforms for skills management, when executed proficiently, enhances capabilities in talent acquisition, retention, and the facilitation of skill advancement. Employing skill assessment tools serves to refine this process, rendering it more streamlined, efficient, and predicated on empirical data (Freise and Bretschneider, 2023). Within Human Resources (HR) technology, there is a notable trend toward integrating AI-based skills management systems. AI-based skills management involves the use of AI technologies to optimize the selection, training, and deployment of personnel based on their skills (e.g., Schlippe and Bothmer, 2023). These systems are designed to deliver bespoke strategic skill evaluations, personalized learning trajectories, and targeted training suggestions (Bersin, 2023). Despite the promise these AI-based skills management frameworks hold, their potential is not fully realized, with the challenges associated with their deployment and utilization uncharted due to barriers (Cubric, 2020). Academia currently lacks sufficient understanding of how to effectively harness these emerging technologies (Allal-Chérif et al., 2021). Nonetheless, the imperative to maintain competitiveness within the skills management sector and to address the emergent needs for re-& upskilling within organizations remains paramount. Accordingly, this paper endeavors to elucidate upon the research question (RQ): *What are challenges in establishing AI-based skill development?*

We apply a qualitative approach to identify these challenges, including interviews with professionals among skills management providers, human resources professionals working in the digital management of skills, and researchers on the topic. Subsequently, we categorize the described challenges into theoretical, conceptual, and practical dimensions and assign a multi-level perspective including systemic, organizational, team, and individual challenges. This paper sets the foundation for understanding the complexities of AI-based skills management and profiling, focusing on essential factors for research and practice for establishing reliable skills profiles and management. The resulting classification scheme relates the dimensions of challenges (theoretical, conceptual, and practical) to levels of consideration at the system, organization, team, and individual levels. This approach outlines the interrelations between dimensions and sheds light on the necessity to include multiple perspectives. We thereby enrich the discussions on the evolving nature of skills profiles in the rapidly changing labor market. Employing a 'proof-of-concept' approach, we highlight unresolved issues in skills management and profiling, crucial to concern for both research and practice (Nunamaker et al., 2015). Our findings and proposed frameworks aim to influence the future direction of skills management amidst ongoing skill transformations.

2 Theoretical Background

2.1 The Influence of AI on Skills in the Working World

Changing job skills due to advances in technology are driving a shift in organizational requirements. AI is one crucial development. AI can be thereby defined as systems that use data and algorithms to mimic human-like cognitive functions, such as decision-making, learning, perception, and reasoning (Baird and Maruping, 2021). Compared to the past, AI is now able to perform many routine tasks independently, such as calculations (Kirkpatrick, 2017). As a result, the adoption of AI has led to re-evaluating human skills, emphasizing the increasing importance of cognitive skills like creativity, critical thinking, communication, and collaboration that complement and enhance AI skills (Whiting, 2020). For instance, the demand for AI skills in software development was highlighted by Păvăloaia and Necula (2023), who notes the importance of both technical and social skills, such as problem-solving and interpersonal communication, for the future of work. Furthermore, Morandini et al. (2023) discuss the critical role of transversal skills in adapting to AI in organizations and highlight strategies to support workers in developing these skills. Accordingly, changing skills require to re-&upskill employees. This highlights the challenge and opportunity for education and training to foster human-centered skills. For example, while AI can take over tasks such as for instance data analysis and decision-making, it still relies on human skills for skills such as critical thinking to interpret the data and to consider the context for decision-making (Samuel et al., 2023). However, while AI may be one of the most prominent drivers of the skill requirements, it brings along opportunities to meet those demands. As people are known to have different abilities (Rychen, 2016), it is necessary to take into account the different skills of employees during the learning process. However, traditional face-to-face evaluations are often limited by the availability of resources and the expertise of staff in the work context. Consequently, the use of AI for personalized recommendations can be beneficial (CEDEFOP, 2017). This is confirmed by several studies examining AI's role in e-learning and education. For instance, AI can provide personalized learning experiences and support for learners with different needs improving the educational process by tailoring educational content and interactions to meet individual learners' unique needs, preferences, and pace (Murtaza et al., 2022; Ritz et al., 2023b).

In addition, the impact of AI on employability and the workforce has been systematically explored, with findings showing that workers need to adapt to new technologies to maintain their employability and professional relevance (Cramarenco et al., 2023). The shift towards skills-based procedures like hiring suggests employers increasingly favor individual skills over formal qualifications, particularly in AI (Gonzalez Ehlinger and Stephany, 2023). Accordingly, managing employee skills presents a challenging task, especially as organizations are faced with considerable pressure to attract and manage professionals (Cantrell et al., 2022). This highlights the importance of strategic choices in skills management that can shape organizational competitive advantage (Broadbent and Weill, 1997; Byrd and Turner, 2000). Integrating AI into skills management within IT-based Human Resources (HR) Management presents significant opportunities to enhance the identification and development of employee skills. This approach is foundational for informed staffing decisions and skill-centric strategies (Dörsam and Körfer, 2021). AI-based analytics can revolutionize skill acquisition and gap analysis, offering organizations insights to efficiently align skills with current and future needs (Cantrell et al., 2022). Additionally, AI in skills assessment provides a more objective analysis of employee capabilities, facilitating tailored development plans (Anwar et al., 2013). The adaptability of AI to different environmental and organizational contexts indicates its potential to keep skills management strategies relevant over time (Garcia-Arroyo and Osca, 2021). However, the effectiveness of AI in skills management hinges on establishing a standardized framework and common language for skills, enabling uniform data interpretation and enhancing system interoperability (Garcia-Arroyo and Osca, 2021; Pospelova et al., 2021). In essence, integrating AI into skills management could revolutionize how organizations approach the development and deployment of employee skills, provided challenges around standardization are addressed. This promises more dynamic, efficient, and personalized HR practices. As Pan and Froese (2023) argue using AI has great potential for HR. Especially on the topic of integrating and establishing AI, more research is needed as this is an aspect often neglected in HR research. This can include challenges in regard to data usage, ethical considerations and technological integration.

2.2 Digitally Mapped Skills Profiles

Exploring the integration of AI in skills management unveils substantial opportunities for enhancing the creation and utilization of digitally mapped skills profiles. A digitally mapped skills profile includes an electronic record individual's skills and experience (Freise and Hupe, 2023). This record typically includes a list of the person's unique skills and abilities, along with information about their experience, education, and training. A profile can also refer to an individual's skillset deemed essential for performing effective job-related tasks, as noted by Sebastião et al. (2023). Employers underline the importance of skills profiles by consenting that when recruiting, they seek candidates who obtain a specific skills profile. The advantages of a skills profile are manifold, including providing a comprehensive view of an individual's skills and qualifications to potential employers or clients, identifying skill gaps, and facilitating the development of training programs (Traynor et al., 2021). The usage of AI in this domain promises to revolutionize how skills profiles are generated, analyzed, and updated. For instance, by automating the aggregation and analysis of skill data, AI can provide dynamic, real-time insights into skill gaps and emerging competencies (Doherty-Restrepo et al., 2023). This extends to the customization of career paths (Ritz et al., 2024), optimizing project staffing (Gerogiannis et al., 2015), and facilitating efficient work allocation (Möhlmann et al., 2021). For example, Zhao et al. (2019b) described an automated skills recognition and normalization system that revealed gaps in skills profiles crucial for matching applicants to the right jobs, and that could be missed by human assessors due to inconsistencies and discrepancies in skills descriptions. Another example is Konstantinidis et al. (2022), who illustrate an approach utilizing deep information retrieval and semantic similarity search for skill identification without the need for human-annotated databases. They introduce an end-to-end method combining text embeddings for skill extraction with a skills graph matching algorithm to compare similar resumes efficiently. Additionally, presenting a consolidated account of one's skills allows for the prioritization of personal development and improvement, serving as a reference point for progress and performance evaluation (Paiva et al., 2022). The creation of a skills profile can be undertaken by the individual or a third party, such as a manager or recruiter, and be in the form of text or graphics, such as lists or graphs. Regular updates are recommended to ensure the alignment of the skills profile with changes in the individual's skills and expertise.

In academia and research, the focus is often on profiles for a specific group of skills like AI literacy (Pinski and Benlian, 2023), occupations like engineering (Pacher et al., 2022), or positions like CIO profiles (Preston et al., 2020). Accordingly, many of these works have primarily concentrated on the theoretical development in one focus area of skills profiles rather than the establishment of exhaustive descriptions of profiles. Similarly, Pospelova et al. (2021) call for reliable and generally applicable skill data. To answer this need, our work addresses the challenges associated with current skills management and skills profiles.

3 Research Approach

Due to the exploratory character of our RQ, we decided on a qualitative research approach. We included ten expert interviews to deepen the understanding of skills management and profiles and to analyze their profound knowledge. The experts were recruited from science and practice in the field of skills management, including researchers, providers, and HR professionals as we consider these groups as promising for expertise and diverse perspectives. The experts are characterized by their intensive engagement with the topic at a scientific level or practitioners who provide extensive experience in interacting with companies and in the implementation of skills management. We applied a semi-structured interview process and conducted online interviews. They took approximately 30 minutes and were recorded and transcribed with prior consent. Based on the literature, we outlined our problem space and defined the relevant concepts to answer the RQ. Afterward, we constructed a semi-structured interview guideline relying on Mayring's (2015) problem-centric approach. The content and questions focused on the experts' perceptions and evaluation of existing skills management and profile approaches. The first interview questions focused on the relevance of skills management and profiles and the development in the last years, followed by a question on the specific work of the expert with skills. Secondly, we asked for the challenges, limits, and non-functional aspects of current skill solutions (e.g., What challenges and opportunities arise from the identification and assessment of skills?). Next, the interview guideline considers the requirements for designing and establishing skills profiles. We concluded with an outlook on use cases and the potential of skills management and profiles. Demographic data was collected, including the experts' position.

Afterward, all transcripts were analyzed along qualitative content analysis using MAXQDA to identify similarities, differences, and overarching themes (Kohlbacher, 2013). Our analysis followed Mayring (2004) approach, starting with generalizing interview material before consolidating it in two reduction steps into resulting statements and insights. Due to the exploratory nature an open coding approach based on Strauss and Corbin's (1990) grounded theory was used to identify and segment pertinent data. Subsequently, axial coding was applied to discern and organize relationships among these codes. Within the interviews, we coded five main categories and seven subcodes and assigned 457 code segments. To conclude the analysis, selective coding was employed to interconnect the previously identified categories that encompass the research findings.

4 Findings

Drawing upon our interviews, we identified three dimensions of challenges. The challenges faced in establishing and utilizing AI in HR extend beyond the practical dimension, encompassing significant theoretical and conceptual issues as well. We refer to a multi-level approach to categorize the challenges of AI in skills profile and management due to the complexity and multifaceted nature of these challenges. Addressing these issues from multiple perspectives provides a comprehensive understanding. We thereby refer to the individual, team, organization, and system level. This categorization is depicted in Table 1. These challenges necessitate not only practical solutions but also research-driven requirements to fully address them.

Table 1. Synthesis of AI-based Skills Management Challenges based on Dimensions and Levels

Dimensions	**Level of Challenges**			
	Individual	Team	Organizational	System
Theoretical Challenge	Preselection of evidence information influencing the data quantity and quality		Consistent semantic skill model within the organization	Solid and reliable data basis for skill categorization
Conceptual Challenge	Transparency of the profile within the organization	Anonymity of skills within the team	Coordinated objectives for skills management	Data protection (rights for access, use, change)

			Data use rights (ownership of data)	
Practical Challenge	Motivation for active use of skills management	Lack of objective rubrics/measures for skills evaluation of peers/ supervisors	Non-skill-ready corporate culture	Integration into existing systems (e.g., personnel management)
	Acceptance of the inherent change process and skills management	Unpredictable group dynamics influencing peer assessments	Adjusting needs to company size	Continuous maintenance of technical functions
	Cognitive distortions biasing self-assessment			

4.1 Theoretical Challenges in Skills Profiles

Theoretical challenges pertain to foundational principles and assumptions, addressing theoretical gaps, and proposing new theoretical frameworks, which require rigorous academic research and critical analysis to advance knowledge.

On the dimension of the theoretical challenges, organizations necessitate the unambiguous articulation of the semantic concept within the organizational framework to delineate the specific evidence information required for establishing a robust and dependable database for subsequent AI-based projects.

The expert interviews shed light on critical aspects of developing and maintaining the data basis on a **system level**. One recurring theme was the challenge of creating a taxonomy or ontology as a data basis for skills, with experts expressing the difficulty of skills as unstructured data. They highlighted the inherent complexity in dealing with language data, particularly in the context of skills. Unlike other data types, language lacking a simple structure poses a significant challenge. The interviewees emphasized the multifaceted nature of skill formulation, citing examples where a skill could be articulated in numerous ways, and its interpretation could vary depending on the context. As expert 1 (E1) stated: *"This is because language in particular is not as simply structured as other data, which means that I can formulate a skill in 50 different ways and some things have a different meaning depending on the context."*. The interviews revealed problems in the development and maintenance of skills management on a system level. These insights, summarized by E3, highlight the crucial role of standardized language in the skill selection process and maintain its relevance: *"I think what you have* *to ensure is the definition and perception of what a skill means in the company."*. Similarly, E9 described the black-box character of skills management providers: "*With the data models behind it with the algorithms, the provider is like a black box. Especially in the sense that it remains unclear whether we can continue to work with this skill data."* (E8). The complexity of language as a data structure for taxonomies is further emphasized by researchers like Donini et al. (1997) and Das et al. (2020). The latter use Latent Dirichlet Allocation (LDA) and the BERT framework for automatic complexity identification, achieving accuracy rates of over 80% in text identification. Further, the risk of the AI being trained on insufficient or flawed data cannot be excluded. Based on the data, the AI could develop biasing decisions, like Amazon's recruiting tool, that showed a bias against women (Reuters, 2018). Therefore, requirement one (R1) states that on a system level a solid and reliable database for skill categorization should be ensured.

At the **organizational level**, the interviews underscored the foundational role of defining skills within a semantic framework. Many organizations struggle with the fundamental question of the concrete skills that are important for them and how to define them in an overarching model like a taxonomy or ontology. In more detail, E2 described the goal that their system should contribute to as crucial because it sets the stage for subsequent processes. *"(…) and I think that is the most important question that many companies still have – 'what exactly do I want?'".* The decision-making process on the organizational level is pivotal, necessitating appropriate expertise and time commitment. This is further highlighted by E10 *"The ever more specific requirements are due to the fact that we are developing so many new technologies and require specialist knowledge that is also becoming ever more specific. That's why we always need new experts."*. This highlights the challenge of necessitating increasingly specialized knowledge and the constant need for new expertise. This situation is closely related to change management theory, particularly the concepts of continuous learning and adaptability in organizational development (Kontoghiorghes et al., 2005). Therefore, R2 includes that on an organizational level, consistent semantic skill models need to developed and integrated into organizational structures.

The critical issue of the pre-selection of evidence on the **individual level** and its influence on the quantity and quality of data is also emphasized: "*That is why we try to collect as much data as possible, which is not always easy. The differences in data quality are enormous."* (E7). We herein suppose this pre-selection occurs at the individual level, which our experts emphasize is usually true. In that case, the sovereignty over this selection lies with the individuals and is potentially susceptible to falsification. The strategy of collecting the most detailed data possible from various sources (e.g., managers and colleagues) is a challenge. However, it contributes significantly to reducing the risks associated with the pre-selection of documents (Freise and Bretschneider, 2023). A broader data set can potentially increase the representativeness and reliability of the results and minimize individual influences. Therefore, we propose R3 as: On an individual level, a preselection of evidence information in terms of quantity and quality should be ensured. Yet, it has to be considered that this aim to include as much data as possible also raises concerns about data privacy and ethical considerations, as sensitive data needs to be stored accordingly.

4.2 Conceptual Challenges in Skills Profiles

Conceptual challenges involve understanding and framing ideas, models, or frameworks, necessitating innovative thinking and clear, coherent concept development.

Organizations are required to contemplate the conceptual framework for the digital management of skills, which encompasses integrating it within existing operational processes and addressing concerns related to data protection. This consideration is oriented towards determining the strategic objectives the organization aims to achieve.

Further, they mentioned data security aspects to take into account on the **system level:** *"(...) of course, data protection issues, i.e., that the data is located in Germany or the EU."* (E4). The citation emphasizes the importance of data security and protection, explicitly highlighting the requirement for data storage localization. R4 underscores the need for skills management systems to integrate robust data security measures, ensuring the confidentiality, integrity, and availability of sensitive information. This adherence to high data protection standards can enhance trust among stakeholders and facilitate compliance with regulatory requirements, thereby supporting sustainable development and maintenance at a system level (Chang et al., 2015).

The experts shed light on the pivotal shift in the **organizational challenge** of providing a strategy toward a more proactive and coordinated approach to skills management. As E7 exemplifies, the focus was initially on identifying deficits in activities, but it evolved to emphasize the importance of future-oriented planning in learning and development. This strategic pivot underscores the complexity of aligning organizational objectives for effective skills management. The *"incredibly long process"* and *"endless discussions at the management level"* (E6) highlight a significant challenge: achieving a uniform understanding and commitment across leadership to implement this strategic shift. This illustrates the requirement five (R5) of clear communication, shared vision, and consensus-building on skills management objectives within an organization. Further, this contributes to a strategic approach towards the possible use cases of skills management: "*With the roll-out plan, we also have to learn about the other use cases in order to drive forward other skill-based topics, such as performance management. If things go well in the first stages if it's not effort without benefit, then you can argue this with our board members."* (E7). Another important challenge that we identified were questions regarding the management, ownership, and ethical considerations of data within organizational platforms. Data quality control and privacy need to be considered. This underscores need (R6) of data use rights, emphasizing the need for governance structures and policies around data ownership, quality control, and protection.

At the **team level**, one challenge mentioned in the interviews pertains to the reliable assessment of team skills when evaluations are conducted anonymously. E1 refers to this as follows: *"One of the problems with assessing teams and employees when everyone evaluates themselves anonymously could be that they don't know how the others evaluate themselves and there is a certain amount of uncertainty. 'Am I evaluating myself correctly or incorrectly?'".* This emphasizes the need for a uniform approach that either includes team comparisons, so that there is a corrective in the assessments (E8) or to ensure anonymity within the evaluation of teams. This translates into the requirement (R7) that the skills of team members and the associated group dynamics should be taken into account.

At the **individual level**, transparency was identified as critical in mitigating concerns. Individuals are more likely to create skills profiles when they perceive transparency in the evaluation process, reducing fears of potential negative consequences based on skill assessments. The statement from E2 underscores the need to balance individual benefit, psychological well-being, and transparent processes to foster engagement at the individual level: *"Acceptance is super relevant. The fact that people think 'This can only be to my disadvantage', especially for low-skilled workers, makes it much more difficult to gain trust. Transparency is also important. If people see that 'I can be checked and then I'm the first to be kicked out because I'm the least qualified, then I don't want to take advantage of that.'"*. The traceability of embedding in existing systems goes hand in hand with this transparency. Similarly, this was examined for knowledge management systems by Ramesh (2002). According to experts, if contextual factors such as time or monetary resources are clearly formulated, it is easier for employees to assess. This is aimed at the selectivity of the individual skills profiles: *"If it is unclear what the individual should be categorized as, motivation drops."* (E7). Therefore, transparency regarding the use of the skills profile needs to be ensured to ensure trust among individuals (R8).

4.3 Practical Challenges in Skills Profiles

Practical challenges are real-world issues encountered during the implementation or application of a solution, such as technical difficulties or resource limitations, requiring tangible solutions.

At the **system level,** the experts refer to skills analysis as one challenge for the skills management provider. The need for a robust maintenance strategy was also emphasized (R9) but described as not being the main point of problems: *"As few regulations as possible, but also as many as necessary*" (E7). Moreover, they directly mention the requirement (R10) of establishing a balance between the lean design of a model and its specificity to accommodate rapid implementation for future use cases within an organization. While meeting the desire for a flexible and adaptable platform to meet immediate and evolving organizational needs, it also needs to be specific enough in its functionalities to support skills management in the stage needed. Accordingly, *"It is necessary to compare the results precisely with those of competitors."* (E8).

One practical challenge at the **organizational level** is having sufficient human resources to propel the initiative forward comprehensively. E5 connects resource investment on the organizational level with the organization's mindset for skills as a holistic topic. This is also reflected in the need to consider differing opinions regarding implementing skills management within organizations. Some individuals may perceive the endeavor as unnecessary, impeding the establishment process. Interestingly, this is more pronounced in larger companies, where the scale of communication and explanation required is substantial: *"Backing from the company that the topic is important and is given the appropriate expertise and time (…). And having enough manpower to drive* *the topic forward is another practical challenge at a high organizational level."* (E5). As a result, organizations need a skill-ready corporate culture to succesfullly build up skills management (R11). Implementing skills management could be straightforward in smaller companies due to fewer stakeholders involved. However, the perceived impact of such systems may be less significant in smaller organizational settings compared to their larger counterparts, as outlined by E2: *"It's much easier in smaller companies. Because you simply have to talk to fewer people and explain less, but I don't think the effects that you can generate are quite as relevant in small companies as they are in large ones."*. This translates into R12, which emphasizes that skills management approaches need to be adjusted to the company size.

Within the **team level**, group dynamics can lead to incorrect evaluations from other team members. This may also be due to insufficient assessment skills by other team members. Accordingly, with the introduction of skills management, teams need to be educated about different assessment methods and need comprehensive evaluation guidelines (R13). Further, the assessment methods within teams can range from evaluations by managers to those conducted by teammates or colleagues from project work. The choice of assessment method introduces additional complexity, with different approaches influencing the evaluation process. This variability underscores the requirement (R13) for clarity and standardization in the assessment procedures to ensure fairness and reliability in team and employee evaluations (Cicchetti, 1994). E7 outlines this: *"But managers in particular are not, in my opinion, in a position to evaluate on the basis or at the level of sub-skills."*.

At the **individual level,** experts emphasized the importance of outlining the added benefit for the individual as a motivating factor for engagement (R14): *"That's perhaps the most important reason. So I should somehow benefit from it and if it only helps my company in some way and not me at all, then I have less motivation to do it."* (E2). They argued that employees experience a reluctance to participate if the benefits were perceived as solely favoring the company rather than contributing to individual growth or well-being. The need to ensure low-threshold access to learning content via mobile devices is also emphasized (R14): *"There are a lot of people who want to access learning content via smartphone, for example, which means you have to make sure that it is used on different devices."* (E9). Moreover, the interviews delved into the psychological dynamics at play, highlighting challenges related to cognitive dissonance phenomena like the Dunning-Kruger effect (i.e., incompetent people overestimate themselves while underestimating the performance of competent people) and impostor syndrome (i.e., people feel inadequate despite their professional success). *"Then you have the problem of narcissists and the impostor syndrome, i.e., people who rate themselves too poorly and people who rate themselves so highly. That can be demotivating."* (E1). The spectrum of self-assessment, ranging from overly critical to overly optimistic evaluations, can lead to demotivation that impacts individuals' engagement and confidence in their skills. Moreover, acceptance emerged as a potential challenge, especially among low-skilled workers. The perception that participation might be detrimental creates challenges in building trust. This can be translated into R15 that organizations need to control for cognitive distortions or group dynamics within self-assessments of skills, for instance by involving peer-assessments as further source.

4.4 Interdependence of Challenge Dimensions

The interdependence of challenge dimensions in skills management highlights the need for a dynamic, iterative approach that connects theoretical, conceptual, and practical aspects. Initially, defining skills clearly is crucial to avoid misunderstandings and establish a solid foundation for organization-wide understanding. Without a clear definition, subsequent phases, especially creating a database for AI initiatives, may face ambiguity. The next step involves tailoring the theoretical framework to the organization's context and needs and integrating it into existing processes. Finally, implementing skills management requires evaluating its effectiveness and acceptance, allowing for the reevaluation of initial theories based on practical insights. Skills management is cyclical, requiring ongoing refinement of strategies based on new insights. E9 highlights this by the requirement for taking an overview and adapting learning based on new insights: *"If we now take a 360-degree view of what someone needs, it is of course important to consider where I come from and where I want to go."*. Like many processes that call for continuous adaption, feedback loops are emphasized in our interview. In more detail, feedback mechanisms enable the reassessment and modification of strategies, ensuring they stay aligned with organizational realities: *"That is why this healthy degree of self-reflection is necessary."* (E9). Maintaining open communication with stakeholders, especially employees and managers allows for adjusting in response to diverse perspectives and unforeseen challenges. This also refers back to the need to outline the inherent value of skills management for all involved parties: *"There are simply many more opportunities for employees themselves, and the more an organization uses its ecosystem for this and opens itself up to the opportunities of skill-based approaches, the more these opportunities multiply."* (E8). The rapid pace of AI advancements necessitates the flexible integration of technologies, necessitating regular updates to both theory and practice: *"So starting with the collection, from the assessments to the training, everything is actually digital. The whole process, there were of course corresponding software tools that were also data protection-compliant and suitable for the collection and for giving feedback and were precisely geared towards this."* (E4). Similar proceeses like change management further support this argumentation (e.g., Galli, 2018).

The levels of analysis, i.e., individual, team, organization and system, although not explicitly mentioned in our interviews, are related as well, influencing each other (Wright and Nishii, 2007).

5 Conclusion

The systematic documentation of an individual's skills, experience, and qualifications offers a comprehensive overview that can significantly enhance various facets of AI-based skills management. We identified challenges at different levels for the successful establishment of skills management. At the system level, creating and maintaining a taxonomy for skills was highlighted. Experts expressed optimism about AI's potential but acknowledged technical issues, emphasizing the intricate nature of language data. On the organizational front, defining skills proves critical, with a focus on the specific goal of the organization. The commitment of expertise, time, and human resources emerged as pivotal. At the team level, the anonymity of self-assessments introduces uncertainty, and the diversity of assessment methods adds complexity, emphasizing the need for standardized procedures. On an individual level, the study highlights the crucial role of personal benefit as a motivator for engagement. Psychological dynamics were noted to impact self-assessments, influencing individuals' confidence and engagement. In summary, effective skills management necessitates addressing challenges at different levels—system, organizational, team-based, and individual. Striking a balance between technological optimism, organizational commitment, fair assessment practices, and individual well-being is integral to successfully developing and utilizing skills.

Our research faces some limitations. Qualitative expert interviews can be prone to subjectivity and bias, where personal views can skew interpretations. This can affect this research in two ways. First, during the expert selection, a bias could have influenced the results, and second, the expert's opinions can be influenced. The small sample size of ten limits the generalizability of findings.

Overall, our paper contributes to scholarly knowledge about skills management frameworks and challenges posed by skills management systems. In the future, our research will not only enhance our understanding of contemporary workforce and skill dynamics but also serve as a basis for developing practical implications for organizations striving to adapt and thrive as skill-based organizations. Future research should also focus on the negative implications of using AI for skills profiles and management to enrich our perspective.

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