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COMPLETING THE SKILLS PUZZLE: DEVELOPING A SKILLS PROFILE DATA MODEL

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Research Paper

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Abstract. In today's working world, driven by technological progress, there is a growing need to adapt and update skills to remain competitive. Employers need qualified employees, and employees want to develop their job-related skills, so skills profiles are becoming more prevalent. These profiles comprise skills that individuals bring to their jobs and develop over employment. When used effectively, they offer benefits in attracting, retaining, and developing talent, as well as in staffing and performance management. This paper proposes a data model for such profiles. Drawing upon a systematic literature review and an interview with employees, we derived the critical aspects of a skill profile data model. We further demonstrate the complexity and the need for a structured approach to include a bottom-up perspective. This research contributes to the theoretical understanding of skills profile data models by including the employee perspectives. It further provides insights for organizations to develop a skilled workforce.

Keywords: Skills Profiles, Data Model, Employee Perspective, Qualitative Research

1 Introduction

The evolving labor markets, characterized by rapid technological advancements, such as artificial intelligence (AI), and digital processes, necessitate a paradigm shift in organizational practices toward skill-based approaches. The current dynamics within these environments underscore the inadequacy of traditional models in addressing the complexities of task allocation and the evolving nature of job requirements (Djumalieva and Sleeman, 2018). Accordingly, employees face two significant challenges. First, there is the challenge of remaining competitive in the job market, necessitating individuals to continuously update and acquire the latest and most relevant skills to fill emerging roles (Jain et al., 2021). Secondly, employees must engage in ongoing development of their current skill sets to align with the demands of 21st century skills, ensuring they can execute their tasks effectively (Lanzl et al., 2024). Despite its importance, integrating complex skills like data literacy into skills profiles remains a challenge (Freise and

Hupe, 2023). In response to these exigencies, data-driven skill profiles have emerged as a promising solution. Skills profiles involve recognizing and developing employees' diverse skills beyond their job roles (Anwar et al., 2013). Nonetheless, the efficacy of such profiles is contingent upon the availability of a robust datamodel, which serves as the foundational element for their successful implementation within organizational contexts. The growing emphasis on lifelong learning and the provision of personalized educational pathways underscores the need for a dynamic, adaptable data model. This model should be capable of mapping out the evolving skill sets required by more complex processes such as AI-integrated work, thereby ensuring that individuals remain competitive in their respective fields (Ritz et al., 2023; Tarafdar et al., 2019). In an increasingly digitized workplace, employees are required to rapid technological advancements and embrace lifelong learning. As these learning requirements are often directed at employees at different levels, the inclusion of their perspectives is of particular relevance to ensure their commitment. Organizations and researchers further support the importance of humans' positions as vital contributors to the overall functioning of the digitized system (Lähteenoja et al., 2021). Therefore, we aim to enhance an employee-focused perspective on the working system. Including an employee's perspective has far-reaching benefits. As Ku et al. (2015) emphasize, perspective-taking helps to navigate social interactions. Also, Litchfield and Gentry (2010) state that it can facilitate knowledge integration, which is considered crucial for organizational learning and innovation. However, the employee perspective on skills is kept out of focus (Slayter and Higgins, 2018). Therefore, we aim to enhance an employee-focused perspective on the working system. A data model focused on skill profiles, informed by employee-driven insights, would cater to the necessity for nuanced skill profile strategies. Leveraging data analytics, such a model empowers organizations to precisely identify, assess, and enhance the varied competencies within their workforce (Kimble et al., 2016). Hence, a detailed examination and outline of a data model for skills management offers the potential for a deeper understanding of prerequisites from a bottom-up perspective. We thereby address the following research question (RQ): *What does a data model look like that integrates employees' perspectives?*

This research introduces a skills profile data model that uniquely derives individual skill data points and their intricate relationships from a literature review (vom Brocke et al., 2009) and qualitative interviews. Unlike existing models that often focus solely on isolated skills, our approach offers a comprehensive framework capturing the complex interconnections of different involved instances within skill sets. This advancement significantly enhances the theoretical foundations of information systems research by providing a more holistic understanding of skills profiles. By elucidating these relationships, the model deepens our theoretical comprehension and facilitates more effective problem-solving methodologies. This offers a new approach for future research and practical applications, thereby providing valuable insights into skills development and deployment dynamics. Our research contributes to the field by incorporating the employee perspective through a bottom-up approach, thereby enriching the existing literature with practical, grounded insights for developing effective skill management strategies. Thereby, our research enriches various management disciplines, including

Information Systems (IS), Data Science, Human Resources (HR), Business Research, Learning, and Education.

2 Background

2.1 Characteristics of Skills Profiles

A skills profile, whether in paper or electronic form, is a record that describes a person's skills and experience. It includes information on their experience, education, and training (Freise and Hupe, 2023). A skills profile provides a holistic overview of a person's skills and qualifications as an overview for themselves or for third parties, such as potential employers or clients (Doherty-Restrepo et al., 2023; Traynor et al., 2021). Thereby, it serves many beneficial purposes. For instance, a compiled account of skills enables the individual to prioritize development and improvement. With the data encapsulated in a skills profile, skill gaps can be detected to give a reference point for progress and performance evaluation (Sebastião et al., 2023) or long-term career path planning (Ritz et al., 2024). Further, the data can be used to optimize and facilitate project staffing (Gerogiannis et al., 2015). These applications can be significantly enlarged by AI developments. For instance, AI can aid in identifying suitable candidates for specific projects and ultimately achieve strategic organizational goals based on data (Chowdhury et al., 2023). A skills profile can be developed by the individual or a third party, such as a manager or recruiter and should be updated regularly to reflect changes in a person's skills and expertise. Thereby, assessment is clearly tied to skills profiles.

However, assessment is not limited to this stage of the employee life cycle. It is also vital to document the status quo of employees' skills in order to provide employees with lifelong learning (Paiva et al., 2022). Some organizations are already investing in managing employee skills more professionally and with the help of AI. In that vein, Microsoft announced the introduction of Viva, an AI-driven qualification service and a multi-channel communication center for employees. With this, Microsoft also recognizes the added value that skill-based approaches provide organizations to increase the engagement and productivity of their employees, which are crucial factors on their path to success (Patton, 2023). Another example of a skills profile is LinkedIn. The usage of these personal profiles has been a significant breakthrough in personnel selection and recruitment (Adams, 2013). Organizations regularly look at applicants' social media presence before making initial hiring selections (van Iddekinge et al., 2016). In this context, it is assumed that profiles enable organizations to learn about an individual's personality, skills, experiences, and values, as well as to assess how well qualifications match job requirements or suit the organization's culture (Bangerter et al., 2012).

In conclusion, skill profiles offer significant benefits to both organizations and employees. However, the ambiguity in data requirements on skills profiles often leads to mismatches between employee expectations and organizational offerings. on employee requirements.

2.2 Enhancing HR Systems with Data-Based Skills Profiles

Existing research is already looking at how to integrate skills or knowledge information in organization-wide HR management systems (Biesalski and Abecker, 2005; Malik et al., 2020). It is argued that skills data often needs to be shared with different HR platforms like SAP (Fteimi and Hopf, 2021; Hirata and Brown, 2008). Therefore, detailed information is not easily used for personnel development. Additionally, the individual proficiency level in skills is difficult to be displayed in HR management systems as it requires constant revision and status updates (Anwar et al., 2013), especially for employees with a long em history in an organization. For instance, a software developer might quickly advance from basic to intermediate proficiency in a new programming language after completing an intensive course, requiring immediate updates in HR systems to reflect this growth accurately. This dynamic nature necessitates sophisticated tracking and frequent updates to maintain accuracy. These aspects should be solved by or supported by information technology. HR systems need to navigate the complexities of skills, which are polysemous, multi-dimensional, and multi-operational. This means that skills like 'communication' can have varying labels, posing evaluation challenges (Markus et al., 2005). Skills are also multi-dimensional, composed of related sub-skills, e.g., project management involves time management and team coordination (Konstantinidis et al., 2022). Furthermore, skills are multi-operational, adaptable across different contexts and may shift focus with job functions (Maurya and Telang, 2017).

Skills-based HR management, including skills profiles, is not a novel concept but rather an underexplored approach (Lawler and Ledford, 1992). The development of the skills-based models has been gradual, evolving from the experiences of organizations recognizing it as a source of competitive advantage (Judrups et al., 2015). While many organizations have incorporated practices aligned with this approach, many still maintain the prevailing job-based approach (Cantrell et al., 2022). Our objective is to elucidate the underlying assumptions and principles of this model and the data structures necessary to establish and fully understand a skills profile. Within skills profiles with consistent data structures, the establishment of a coherent and comprehensive model is essential to effectively capture, assess, and utilize skills and subskills (Fernández-Sanz et al., 2017) . Structuring skills profiles is equally crucial for HR management and talent development (Nikitinsky, 2016). In this regard, the interplay between skills, subskills, evaluation methods, and proficiency levels can be visualized as a data model, where each component contributes to the accuracy and utility of skills profiles. This model would serve as the basis for constructing and navigating the landscape of skills assessment and development, offering a clear reference point for evidence-based decision-making in workforce development. A good starting point for this is given by Hirata and Brown (2008), who outlined a skill-competency management architecture to improve HRs information systems. However, we aim to further build upon existing literature and interview data, tailoring it to the specific case of skills profiles. The model should symbolize the interdependent organization of skills, subskills, evaluation methods, proficiency levels, usage contexts, and their connections, resembling a structured data model to emphasize the importance of skills profiles.

3 RESEARCH APPROACH

3.1 Data Collection

We used a two-folded qualitative research approach to examine our RQ. The aim is to shed light on the requirements for skills profiles from an employee perspective. Based on a comprehensive understanding of the role of skills in everyday working life, we want to evaluate the most important dimensions for conceptualizing skills profiles. Finally, these aspects will be translated into requirements that employees place on mapping their skills. We conducted a systematic literature review following the methodology of vom Brocke et al. (2009), targeting articles within IS, management studies, and education across four digital libraries: AISeL, ScienceDirect, ProQuest, and Web of Science. Our search strategy utilized key terms related to skills management, skills profiles and data models or data structures, adapted semantically for each database. We included English-language articles published between 2010 and January 2023, initially identifying 93 articles from titles, abstracts, and keywords. After screening for relevance and excluding duplicates or texts without full-paper access, we narrowed the selection to 50 publications. Further refinement excluded papers wich did not directly refer to a specific skill or data, resulting in 21 papers. Final inclusion criteria led to 17 studies focused on developing data models on skills profiles of professional skills in adult education or workplace settings, evaluating more than one skill or competency. Additional searches on Google Scholar added two more studies, totaling 19 publications for detailed analysis. The detailed process is displayed in Figure 1.

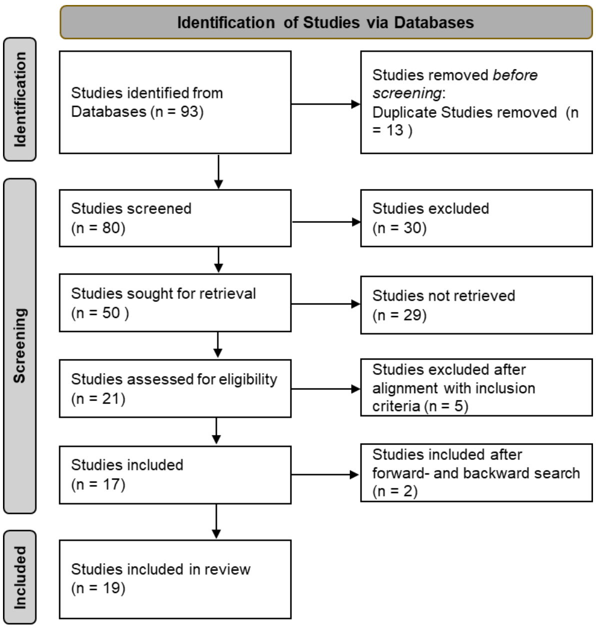

Figure 1. Literature Review Process according to the PRISMA Framework

The second part of our research consists of interviews based on a semi-structured questionnaire (Mayring, 2004). The semi-structured questionnaire allows for a deeper and more nuanced analysis of the reported data (Bell et al., 2022). The interview guide was created in eight steps: (1) defining the research area, (2) developing specific research questions, (3) determining the interview topics, (4) formulating the interview guide, (5) revising the questions, (6) conducting a mock interview, (7) identifying further guiding questions and (8) finalizing the guide (Bell et al., 2022). The first section of the questionnaire collects demographic details, such as educational background and current job, to understand the professional context. The second section explores the application of skills in participants' jobs, identifying crucial skills and their usage in different contexts. The third section assesses perceptions of individual skills, including the importance of according to proficiency levels. Additionally, it explores the systematic resources and organizational support participants utilize or require to enhance or broaden their skill set. The final section of the questionnaire explores participants' experiences with skill development over their careers and their perspectives on the future evolution of skills in their work, focusing on anticipated changes in requirements.

A total of 20 participants from different work backgrounds, age groups, and hierarchical levels in organizations were interviewed to generate a meaningful sample. The interviews were conducted according to theoretical saturation, i.e., further data collection does not provide new insights into the research issues (Glaser and Strauss, 1967). They took approximately 30 minutes and were recorded and transcribed with prior consent. The average age was 35 years (34.8 years). 65% of the participants classified themselves as male and 35% as female. 15% of the participants had a secondary school certificate, 35% a high school diploma, 35% a bachelor's degree, and 15% a master's degree. The interviews revealed that 25% of participants are working students, 55% are regular employees and 20% are managers with leadership responsibilities. The participants worked in the Customer Quality Department, Test Planning, Engineering, Sales, Administration, Compliance, Customs, IT Project Management, and HR.

3.2 Data analysis

Subsequently, the transcripts were examined, and a qualitative content analysis was carried out using MAXQDA. This process aimed to identify similarities, differences, and key themes in the data set. Our analytical method was guided by Mayring (2004), starting with the generalization of interview content, followed by two reduction stages to distill the material into final observations and conclusions. In line with grounded theory's established methods, we employed open, axial, and selective coding as outlined by Charmaz and Belgrave (2012) and Strauss and Corbin (1990), further supported by Saldana (2021) techniques in these coding processes. Within the 20 interviews, we coded four main categories and 15 subcodes and assigned 597 code segments.

4 RESULTS & DISCUSSION

4.1 Literature-based Skills Profile Data Model

Based on our literature review, we developed a conceptual data model that involves an abstract representation of data in accordance with Batra and Marakas (1995). To achieve this, we started by conducting a comprehensive literature review to identify core papers and extract relevant data elements. Then, we systematically categorized these elements as higher-level constructs and noted their connections. Thereafter, we developed a conceptual model using visualizations, ensuring all necessary data elements and relationships are accurately represented.

When considering the data structure of skills profiles, it becomes apparent that evidence about skills, such as certificates, CVs, references, or micro-credentials, is required to validate the evaluation process, which in turn tracks this information (Gottipati and Shankararaman, 2018). In this stage, natural language processing techniques are already established. For instance, Fareri et al. (2020) and Lula et al. (2018) used a text-mining method to identify semantic components from job descriptions. Methods like these produce a rich repository of recorded content demonstrating the individual's skills in different use contexts or areas of expertise. This is emphasized by Sciuk and Hess (2022), who distinguish between role-related and general skills. The use context provides essential skill-specific details necessary for correct evaluation. For instance, data literacy in business analytics might be assessed via KPI analysis (Ridsdale et al., 2015).

In contrast, in scientific contexts, it could focus on experimental analysis, statistical testing, and preparing publications. The models' proficiency levels indicate varying degrees of mastery (Pellegrino, 2013). These levels differentiate the person's skills and subskills and inform their progress in a certain domain. One framework that particularly refers to proficiency levels is the Digcomp model (Carretero et al., 2017). Therein, the complexity of tasks, as well as the employee's autonomy in applying the skill, is considered. Next, the different skills are not isolated but interconnected with other skills, forming a network that can be represented in ontologies or taxonomies (e.g., Fazel-Zarandi and Fox, 2013; European Commission, 2022). For example, a person with high ability in networking is likely to also show high ability in teamwork and negotiation, as shown by Pospelova et al. (2021). This outlines the need to consider related skill aspects in addition to the core skill set. Moreover, the skill relations together shape a semantic skill model. Within our literature review, Bendler and Felderer (2023) developed a competency model for IS and cybersecurity and argue for a better understanding of the relation between skill categories like social and methodological skills. A structured semantic skill model can assess an individual's proficiency across contexts like marketing, healthcare, or finance. It aligns evidence like certifications and project outcomes with skill proficiency standards, offering a solid basis for evaluating skills across professional fields.

Nevertheless, it needs to be considered that the data model described here mainly relies on research that includes the organizational perspective but not the employee perspective. In other words, it does not take into account what employees actually consider important for their skill assessment and development.

4.2 Employee Requirements for a Skills Profile Data Model

This section delves into the requirements that emerged from the qualitative interviews. We describe the employee perspectives in detail and provide exemplary quotes from the participants. Moreover, we position them in relation to our previously proposed data model. Each of these requirements contributes to a bottom-up understanding of skills' pivotal role in education, career development, and organizational success. By examining employee perspectives, we provide additions to our data model on skills profiles and enlarge the concrete use context applications for technology.

Identification of Skill Requirements: This involves systematically gathering and defining the skills needed in a particular job role or industry. This could be done through a rigorous analysis of job descriptions, industry standards, and skill models. One key element of this requirement on a skills profile is the semantic skill model that guides further development. This is outlined by a statement that highlights the multidimensional nature of skills like data literacy. As participant 7 (P7) states: *"I am not sure, I would say using the right data, the right way at the right time."*. To be as in this example, data literate, individuals must possess a blend of technical skills, critical thinking, and domain-specific knowledge to maximize the value of data in their respective roles and industries. This requirement was already described by Bibi et al. (2021), who discuss a framework for calculating employees' soft and hard skills, enhancing task assignment based on worker's skills. They describe that existing skill management is often based on job descriptions as the data basis that organizations can easily build upon to identify the skills needed for a position or a task. A longitudinal approach is described by Longenecker et al. (2013). They used curricula to identify changes in skills and the required subskills for IS over a fifty-year period. Referring to our profile model, this confirms the need for a semantic skill model that offers a general common understanding of the construct that is referred to in the evidence information.

Modeling and Structuring Skills Data: Following the principles of requirements data modeling, the gathered skills can then be organized into a structured format. This could involve categorizing skills into different areas such as technical, interpersonal, cognitive, and others. Each skill can be further defined with attributes like proficiency level required, relevance to specific job roles and use context, and interdependencies with other skills. As outlined in the interviews, many employees face difficulties in the evaluation of their own skills, especially because they do not have a systemized understanding of the different sub-skills and the concept behind. *"That depends, of course, on which skills we are talking about. Are we talking about technical skills or about the job?"* (P12). Databases like O*NET (The Occupational Information Network) from the U.S. Department of Labor/Employment and Training Administration (2022) and ESCO (European Skills, Competences, Qualifications, and Occupations) by the European

Commission (2022) provide extensive collections of skill-related information, comprising numerous entries. However, the existence of these databases highlights the need to construct a data model that focuses on individual skills. This model is essential for accurately representing and establishing a robust conceptual basis for subsequent actions. In reference to our model, this requirement is related to the domain of skills and their contribution to the design of a semantic skills model.

Dynamic Update and Management: A skills profile model must allow easy updates and modifications. This aspect is crucial given the rapidly changing nature of job requirements and skill sets in the modern workplace. As P14 describes, it is challenging to keep up with changing requirements and regulations about data, so a skills profile and the underlying model need to be adaptable and flexible enough to stay up pace *"the challenge lies in being able to cope with the ever-increasing volume of data. (...) In addition, there are always system updates, and it feels like there are always new systems being added and I think the most difficult thing is to keep learning and always be up to date."*. Global organizations are facing increasing challenges in efficiently managing the skills of their employees (Minku et al., 2013). In order to keep comprehensive records of employees' skills, experience, and knowledge, effective software support with detailed profiles of all employees is essential (Bibi et al., 2021). This enables tracking employees' changing skill sets and managing them efficiently for different purposes. Within our data model, this becomes particularly important in updating the definitions of skills and related skills based on changes or refinements in the semantic skills model. . If those are constantly feedbacked and kept up-to-date, the subsequent steps can be accordingly adapted.

Integration with HR and Organizational Systems: The model could be integrated into human resource management systems, aiding in tasks like recruitment, employee development, and career planning. By aligning skills profiles with organizational needs and individual career paths, the model can support both strategic HR planning and personal development. This part is something that organizations struggle with, as emphasized by this statement: *"Our processes are still relatively unstructured, and you have to have a hands-on mentality to keep track of things."* (P16). The need for a holistic system is further illuminated by P6, who argues for as few independent solutions as possible but rather one HR system so that people do not have to be accustomed to many stand-alone programs. Similarly, many organizations are already transforming their HR management systems to more strategic HR Information Systems that include functions like HR planning, meaning to analyze learning. Nagendra and Deshpande (2014) showed that those systems increase the efficiency and effectiveness of HR through the integration of skills inventories and the combination with an analysis of unfilled job positions. They also stress the need for an integrated personnel system to benefit organizations. At this point, the requirements named in our interviews extend beyond the profile model and are referring to an even broader context that is important to consider in skills management. Similarly, Holland and Fathi (2005) argue for integrating skill graphs into HR management systems and Fteimi and Hopf (2021) emphasize the same for knowledge management.

Analytical Insights and Gap Analysis: By using the data provided by, for instance, assessments and evidence like CVs in the skills profile model, organizations can perform detailed analyses to identify skills gaps, predict future skill requirements, and plan necessary training and development interventions. *"It would also be interesting to find out about other analysis tools or the possibilities of simply obtaining more and more useful evaluations using current tools."* (P16). P18 describes a positive example. In this case, if the person had skill gaps, they wouldn't have to worry about keeping up to date themselves but would receive the necessary support from the company. To develop this aspect further, it would ideally be data-based, possibly automated, and therefore independent of individuals. This could be realized by online learning platforms that gather extensive data on the learning process. This includes how learners engage with course materials via system access patterns and video consumption habits (Santandreu Calonge and Aman Shah, 2016). In addition, analysis of this data provides practical insights into potential individual or organization-wide skills gaps (Laboissiere and Mourshed, 2017) and can inform long-term decision-making processes such as strategic workforce planning (Cotten, 2007). The availability of data from online settings is essential for this step and confirms the domains of the data model. Insights into actual and target states at the skill level offer the possibility of concluding necessary further training in the context of use at the proficiency level.

Personalization and Individual Development Plans: Employees can use the model to understand their current skill levels, identify areas for improvement, and align their personal development goals with organizational needs. This is outlined by P*8 "In any case, targeted and planned and also implemented training measures which, depending on the data relationship concerned, are also implemented or generally made available for the time being, i.e. training measures in general."*. Further, P6 emphasizes the challenge of *"(...) learning the right things (...)",* as a lot of information is often offered that is not relevant to individual needs. These statements emphasize the need for well-designed, customized, and relevant skill training programs. Such training should consider individuals' unique challenges and provide them with the skills and knowledge necessary to make informed decisions and contribute effectively to their roles within an organization. Additionally, training should be agile and adaptable to evolving needs and technology advancements, ensuring that individuals are well-prepared to navigate the complexities of the data-driven world. This finding aligns with Brinton et al. (2015), who call for a shift from on-site to online training as they promise a high potential for personalized and interactive learning journeys. Further, employees should be able to develop more self-directed. Self-regulated learners can independently control their learning by setting goals and choosing effective strategies (Zimmerman, 2002). Prior research emphasized that adult education catalyzes empowerment (Boyadjieva and Ilieva-Trichkova, 2023). Consequently, courses to improve and enhance skills should enable learners to take charge of their skill development (Boyadjieva and Ilieva-

Trichkova, 2023). Personalized learning journeys can be designed in various ways and are known as effective strategies to support learners (Ritz et al., 2024). Based on the previously based skill gaps in use context and proficiency level, these personalizations can be enabled and can be incorporated into a re-evaluation of skills.

Overall, our findings confirm and extend many domains of the data model outlined based on the literature. The data model shown in Figure 2 represents the addition of the employee perspective. Such a model could help align employee skills with evolving industry requirements and individual career aspirations.

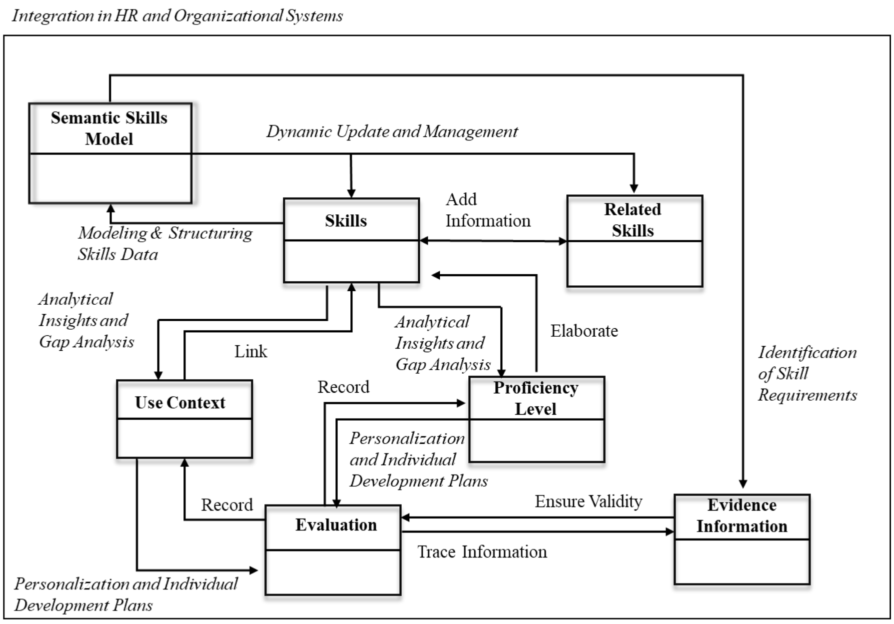

Figure 2. Skills Profile Data Model including to the Employee Perspective

5 LIMITATIONS & FUTURE RESEARCH AVENUES

Our findings, while insightful, have limitations, highlighting areas for further research. Methodologically, the reliance on a small sample of 20 participants limits the generalizability and depth of the insights gained (Marshall et al., 2013). The size limits the representation of diverse opinions and experiences, potentially introducing bias. Despite efforts to ensure diversity among the participants regarding job positions, age, and gender, the limited demographic range may not fully capture diversity (McIntosh and Morse, 2015). Additionally, the potential for socially desirable responses could skew the results (Bergen and Labonté, 2020). Future research with larger and more diverse samples is needed for broader validation. Second, the absence of direct application in organizational settings limits the practical verification of our data model. This gap points to the need for empirical research that tests these models in practice, enhancing the relevance and applicability of our conclusions in organizational contexts.

For future research, the integration of AI in candidate selection raises questions about the necessity of structured data. While AI can process unstructured data, structured data ensures accuracy, transparency, and fairness, addressing ethical concerns and employee requirements. Future research can examine the optimal data structures for AI-based skills profiles in more detail. Moreover, research could examine what drives the acceptance and engagement with skill assessments. Longitudinal research is crucial for tracking how skill profiles adapt to changes in technology, the market, and demographics and assessing the sustainability of current models. Ethical issues, such as data privacy, assessment bias, and responsible data use, are critical areas to ensure fairness and transparency in skill management. Addressing these topics will improve our knowledge of skill management, enhance skill profile models, and help organizations optimize their workforce's skills. By pursuing these future research directions, scholars can contribute to optimizing skill sets and completing the skills puzzle.

6 CONCLUSION

Accurately measuring and developing employee skills is of paramount importance, especially in the context of the changing world of work. Therefore, it is essential to understand the underlying concepts, possible methods, and requirements of employees for a system that should support them in skills development. This research paper provides an understanding of the needs of employees for skills profiles. Furthermore, the insights from our interviews are broadened and used to develop and evaluate the data model for a skills profile model based on existing literature. We thereby present six different requirements that are emphasized for a holistic skills profile. Our work contributes to a better understanding of employees' perspectives on skills management and their needs in such a system. Overall, the results provide a deeper insight into how skills profiles can be designed and which underlying dimensions of skills are vital. In doing so, we enrich the literature on skills profiles from a bottom-up perspective. In addition, this overview provides actionable guidance for practitioners on what approaches can create a reliable and objective recording of employee skills. Based on this, it can empower employees to develop their skills independently, equip organizations with the necessary knowledge to use their employees' skills best and identify suitable development paths. It should facilitate continuous learning, skill gap analysis, and the development of complementary skill sets.

7 REFERENCES

Adams S (2013) New survey: LinkedIn more dominant than ever among job seekers and recruiters, but Facebook poised to gain. *Forbes*, 2013, 28–29.

Anwar Z, Bibi N and Ahsan A (2013) Expertise based skill management model for effective project resource allocation under stress in software industry of Pakistan. In: *6th International*

Conference on Information Management, Innovation Management and Industrial Engineering: Xi'an, China, 23.11. 2013 - 24.11.2013, pp. 509–513. Piscataway, NJ: IEEE Service Center.

Bangerter A, Roulin N and König CJ (2012) Personnel selection as a signaling game. *The Journal of applied psychology* 97(4): 719–738.

Batra D and Marakas GM (1995) Conceptual data modelling in theory and practice. *European Journal of Information Systems* 4(3): 185–193.

Bell E, Bryman A and Harley B (2022) *Business research methods*. Oxford University Press.

Bendler D and Felderer M (2023) Competency models for information security and cybersecurity professionals: analysis of existing work and a new model. *ACM Transactions on Computing Education* 23(2): 1–33.

Bergen N and Labonté R (2020) “Everything is perfect, and we have no problems”: detecting and limiting social desirability bias in qualitative research. *Qualitative health research* 30(5): 783–792.

Bibi N, Anwar Z and Rana T (2021) Expertise based skills management system to support resource allocation. *PLoS ONE* 16(8): e0255928.

Biesalski E and Abecker A (2005) Integrated processes and tools for Personnel Development. *2005 IEEE International Technology Management Conference (ICE)*: 1–8.

Boyadjieva P and Ilieva-Trichkova P (2023) Adult Education as a Pathway to Empowerment: Challenges and Possibilities. In: Holford, J., Boyadjieva, P., Clancy, S., Hefler, G., & Studená, I. (ed) *Lifelong Learning, Young Adults and the Challenges of Disadvantage in Europe:* Palgrave Macmillan, Cham, pp. 169–191.

Brinton CG, Rill R, Ha S, et al. (2015) Individualization for Education at Scale: MIIC Design and Preliminary Evaluation. *IEEE Transactions on Learning Technologies* 8(1): 136–148.

Cantrell S, Griffiths M, Jones R, et al. (2022) The skills-based organization: A new operating model for work and the workforce. *Deloitte*, 8 September.

Carretero S, Vuorikari R and Punie Y (2017) *DigComp 2.1: The digital competence framework for citizens*.

Charmaz K and Belgrave L (2012) Qualitative interviewing and grounded theory analysis. In: Gubrium JF (ed) *The SAGE Handbook of Interview Research: The Complexity of the Craft:* SAGE, pp. 347–365.

Chowdhury S, Dey P, Joel-Edgar S, et al. (2023) Unlocking the value of artificial intelligence in human resource management through AI capability framework. *Human Resource Management Review* 33(1): 100899.

Cotten A (2007) *Seven steps of effective workforce planning*. IBM Center for the Business of Government.

Djumalieva J and Sleeman C (2018) An Open and Data-driven Taxonomy of Skills Extracted from Online Job Adverts. In: Larsen C, Rand S, Schmid A and Dean A (eds) *Developing Skills in a Changing World of Work:* Rainer Hampp Verlag, pp. 425–454.

Doherty-Restrepo JL, Perez K, Creeden M, et al. (2023) Closing the Gap Between Students' Career Readiness and Employers' Expectations. *International Journal of Innovative Teaching and Learning in Higher Education* 4(1): 1–14.

European Commission (2022) ESCO. Available at: https://esco.ec.europa.eu/de (accessed 28 September 2022).

Fareri S, Fantoni G, Chiarello F, et al. (2020) Estimating Industry 4.0 impact on job profiles and skills using text mining. *Computers in Industry* 118: 103222.

Fazel-Zarandi M and Fox MS (2013) Inferring and validating skills and competencies over time. *Applied Ontology* 8(3): 131–177.

Fernández-Sanz L, Gómez-Pérez J and Castillo-Martínez A (2017) e-Skills Match: A framework for mapping and integrating the main skills, knowledge and competence standards and models for ICT occupations. *Computer Standards & Interfaces* 51: 30–42.

Freise LR and Hupe A (2023) Transferring Digital Twin Technology on Employee Skills: A Framework to Support Human Resources. In: *83rd Academy of Management Annual Meeting:* Boston, MA, USA.

Fteimi N and Hopf K (2021) Knowledge Management in the Era of Artificial Intelligence: Developing an Integrative Framework.

Gerogiannis VC, Rapti E, Karageorgos A, et al. (2015) A fuzzy linguistic approach for human resource evaluation and selection in software projects. In: *Proceedings of the 2015 International Conference on Industrial Engineering and Operations Management (IEOM):* Dubai, 3 - 5 March 2015. IEEE.

Glaser B and Strauss AL (1967) *Discovery of Grounded Theory: Strategies for Qualitative Research*. Somerset: Taylor and Francis.

Gottipati S and Shankararaman V (2018) Competency analytics tool: Analyzing curriculum using course competencies. *Education and Information Technologies* 23(1): 41–60.

Hirata K and Brown M (2008) Skill-Competency management architecture. In: *Proceedings of the 16th International Conference on Computers in Education:* pp. 179–185. Citeseer.

Holland A and Fathi M (2005) Creating Graphical Models as Representation of Personalized Skill Profiles. *2005 IEEE International Conference on Systems, Man and Cybernetics* 1: 560–565.

Jain H, Padmanabhan B, Pavlou PA, et al. (2021) Editorial for the special section on humans, algorithms, and augmented intelligence: The future of work, organizations, and society. *Information Systems Research* 32(3): 675–687.

Judrups J, Zandbergs U and Kazakovs M (2015) Competence based human resource development solution. *Engineering for Rural Development* 14: 669–674.

Kimble C, Vasconcelos JB de and Rocha Á (2016) Competence management in knowledge intensive organizations using consensual knowledge and ontologies. *Information systems frontiers a journal of research and innovation* 18: 1119–1130.

Konstantinidis I, Maragoudakis M, Magnisalis I, et al. (2022) Knowledge-driven Unsupervised Skills Extraction for Graph-based Talent Matching. In: *Proceedings of the 12th Hellenic Conference on Artificial Intelligence:* Corfu Greece, 07 09 2022 09 09 2022. New York, NY, USA: ACM.

Ku G, Wang CS and Galinsky AD (2015) The promise and perversity of perspective-taking in organizations. *Research in Organizational Behavior* 35: 79–102.

Laboissiere M and Mourshed M (2017) Closing the skills gap: Creating workforce-development programs that work for everyone. *McKinsey & Company* 2.

Lähteenoja V, Flanagan AJ and Warren S (2021) *On the Importance of Human-Centricity and Data*.

Lanzl J, Schnaak F, Schöttl F, et al. (2024) Der Einfluss von digitalen Technologien auf Wissensarbeit: Kompetenzen im Wandel. *HMD Praxis der Wirtschaftsinformatik* 61(1): 141–158.

Lawler E and Ledford G (1992) A skill-based approach to human resource management. *European Management Journal* 10(4): 383–391.

Litchfield RC and Gentry RJ (2010) Perspective-taking as an organizational capability. *Strategic Organization* 8(3): 187–205.

Longenecker H, Feinstein DL and Clark J (2013) Information Systems Curricula:A Fifty Year Journey. *Information Systems Education Journal* 11: 71–95.

Lula P, Oczkowska R, Wiśniewska S, et al. (2018) Ontology-based system for automatic analysis of job offers. In: *The 12th Professor Aleksander Zelias International Conference on Modelling and Forecasting of Socio-Economic Phenomena:* pp. 256–265.

Malik A, Froese FJ and Sharma P (2020) Role of HRM in knowledge integration: Towards a conceptual framework. *Journal of Business Research* 109: 524–535.

Markus L, Thomas HC and Allpress K (2005) Confounded by competencies? An evaluation of the evolution and use of competency models. *New Zealand journal of psychology* 34(2): 117.

Marshall B, Cardon P, Poddar A, et al. (2013) Does sample size matter in qualitative research? A review of qualitative interviews in IS research. *Journal of computer information systems* 54(1).

Maurya A and Telang R (2017) Bayesian multi-view models for member-job matching and personalized skill recommendations. In: *2017 IEEE International Conference on Big Data (Big Data):* Boston, MA, 11 - 14 December 2017, pp. 1193–1202. IEEE.

Mayring P (2004) Qualitative Content Analysis. In: Jenner B, Flick U, Kardoff E von and Steinke I (eds) *A companion to qualitative research:* SAGE.

McIntosh MJ and Morse JM (2015) Situating and constructing diversity in semi-structured interviews. *Global qualitative nursing research* 2: 2333393615597674.

Minku LL, Sudholt D and Yao X (2013) Improved evolutionary algorithm design for the project scheduling problem based on runtime analysis. *IEEE Transactions on Software Engineering* 40(1): 83–102.

Nagendra A and Deshpande M (2014) Human Resource Information Systems (HRIS) in HR planning and development in mid to large sized organizations. *Procedia - Social and Behavioral Sciences* 133: 61–67.

Nikitinsky N (2016) Improving talent management with automated competence assessment: Research summary. In: *Scientific-Practical Conference" Research and Development":* pp. 73–82.

Paiva JC, Leal JP and Figueira Á (2022) Automated Assessment in Computer Science Education: A State-of-the-Art Review. *ACM Transactions on Computing Education* 22(3): 1–40.

Patton S (2023) Introducing Skills in Microsoft Viva, a new AI-powered service to grow and manage talent. Available at: https://www.microsoft.com/en-us/microsoft-365/blog/2023/10/10/introducing-skills-in-microsoft-viva-a-new-ai-powered-service-to-grow-and-manage-talent/ (accessed 5 January 2024).

Pellegrino JW (2013) Proficiency in science: Assessment challenges and opportunities. *Science* 340(6130): 320–323.

Pospelova V, Baldominos IL, Sanz LF, et al. (2021) Big Data and Skills Frameworks to Determine Recommended Profiled of Soft Skills for IS Development. *Proceedings of the International Conference on Information Systems Development (ISD)*.

Ridsdale C, Rothwell J, Smit M, et al. (2015) Strategies and best practices for data literacy education: Knowledge synthesis report.

Ritz E, Donisi F, Elshan E, et al. (2023) Artificial Socialization? How Artificial Intelligence Applications Can Shape A New Era of Employee Onboarding Practices. In: *56th Hawaii International Conference on System Sciences (HICSS):* Waikiki, Hawaii, USA.

Ritz E, Freise L, Elshan E, et al. (2024) What to Learn Next? Designing Personalized Learning Paths for Re-&Upskilling in Organizations. In: *Hawaii International Conference on System Sciences (HICSS):* Waikiki, Hawaii, USA.

Saldana J (2021) *The coding manual for qualitative researchers*. Sage Publications Ltd.

Santandreu Calonge D and Aman Shah M (2016) MOOCs, graduate skills gaps, and employability: A qualitative systematic review of the literature. *International review of research in open and distributed learning* 17(5): 67–90.

Sciuk C and Hess T (2022) Governing digital transformation–The profiles of top managers. In: *Pacific Asia Conference on Information Systems:* p. 1.

Sebastião L, Tirapicos F, Payan-Carreira R, et al. (2023) Skill Profiles for Employability: (Mis)Understandings between Higher Education Institutions and Employers. *Education Sciences* 13(9): 905.

Slayter E and Higgins LM (2018) Hands-On Learning: A Problem-Based Approach to Teaching Microsoft Excel. *College Teaching* 66(1): 31–33.

Strauss A and Corbin J (1990) *Basics of Qualitative Research: Grounded Theory Procedures and Techniques*. London: SAGE.

Tarafdar M, Beath CM and Ross JW (2019) Using AI to enhance business operations. *MIT Sloan Management Review* 60(4).

Traynor S, Wellens MA and Krishnamoorthy V (2021) Job Profile Builder. In: Traynor S, Wellens MA and Krishnamoorthy V (eds) *SAP SuccessFactors Talent: Volume 1:* Berkeley, CA: Apress, pp. 65–111.

U.S. Department of Labor/Employment and Training Administration (2022) Occupational Information Network (O*NET). Available at: https://www.onetcenter.org/ (accessed 28 September 2022).

van Iddekinge CH, Lanivich SE, Roth PL, et al. (2016) Social Media for Selection? Validity and Adverse Impact Potential of a Facebook-Based Assessment. *Journal of Management* 42(7): 1811–1835.

vom Brocke J, Simons A, Niehaves B, et al. (2009) Reconstructing the giant: On the importance of rigour in documenting the literature search process. In: *17th European Conference on Information Systems:* Verona, Italy, pp. 2206–2217.

Zimmerman BJ (2002) Becoming a Self-Regulated Learner: An Overview 41.