Automized Assessment for Professional Skills – A Systematic Literature Review and Future Research Avenues

Research Paper

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Abstract. Globalization, technological progress, and demographic trends increasingly influence our labor markets. With changing labor markets and increasing digitalization, new competencies of workers are needed to meet demands. However, as a first step to developing these new skills, knowledge about the existing skills and their status quo is necessary. Here, automated skill assessment offers a crucial added value, as it can create a reliable and objective database. Based on a systematic investigation, our analysis shows, in four different areas, how skills and competencies in the automated assessment are (1) defined, (2) included as an element of analysis, (3) methodically recorded and processed, (4) which data source is used. In doing so, we offer insights into existing approaches to automated assessment of professional skills. We contribute to a better understanding of the design of automated skill assessment methods and provide perspectives on future research directions.

Keywords: *Data Reliability, Automated Skill Assessment, Natural Language Processing, Literature Review.*

1 Introduction

A growing amount of research studies predict that globalization, technological developments, and demographic trends will reshape our labor markets (OECD, 2018; Merchel *et al.*, 2021). Bakhshi *et al.* (2017) argue that future skills will be favored not only by automation but by personnel shortages. These skills include interpersonal, higher-order cognitive, and system skills and will require transferable skills such as metacognition to perform tasks (World Economic Forum, 2018). To date, professional skill assessment relies on subjective evaluation from, e.g., supervisors, teammates, or task performance (Judrups *et al.*, 2015; Petrov, 2020). This process requires substantial resources like working time from Human Resources (HR) (Gorlov *et al.*, 2015) and lacks reliability and objectivity, i.e., no influence from others.

Although innovative HR methods exist to capture skills automatically, like natural language processing (NLP), a systematic overview of the opportunities for employers and employees is missing. Four main challenges comprise skill assessment (Rayón *et al.*, 2014): a lack of scalability, the subjectivity of interpretation by evaluators, a difficulty finding latent skills behind activities, i.e., the operationalization of skills, and a lack of appropriate and applicable assessment methods. Accordingly, existing methods may not approach skill assessment with objectivity and reliability (Sander *et al.*, 2020). As assessing the required skills for the 21st-century constitutes a challenge (Judrups *et al.*, 2015), new approaches to support employees' skill development are discussed. Nevertheless, the diversity of new skills poses new demands on assessments, which need to capture more prosperous and complex skills (Rayón *et al.*, 2014). Automated assessment is a potential solution to this problem. The increased availability of skill data enables technologies to capture and group skills and relate them to other processes like re- and upskilling. For example, NLP and algorithmic work improvement have been shown in labor market studies (Fareri *et al.*, 2020). However, there is a lack of comprehensive reviews on applied automated skill assessment methods for professionals. Thus, this study aims to answer the research question: *RQ: What is the state-of-the-art regarding automized skill assessment of professionals, and what future research avenues can be identified?*

A systematic literature review following Webster and Watson (2002) and Vom Brocke *et al.* (2009) will be conducted to answer the research question. We aim to give an overview of automized skill assessment for employees in Information Systems (IS) research and related research like HR, Education, Management, and Organizational Behavior. The analysis focuses on skill definition, assessed skills, assessment approaches, data source, and results of the retrieved papers. We will summarize the most important findings and consolidate existing literature. This holistic literature review identifies research gaps, inconsistencies, and unresolved questions within the existing body of knowledge, thereby suggesting potential avenues for future research that will advance the scientific discourse on automated skill assessment.

2 Related Work

2.1 Definition of Professional Skills and Competencies

The conceptualization of skills and competencies has been subject to extensive research for nearly a century (e.g., Seashore, 1930). However, the definition remains unclear, mainly due to the difficulty delineating related concepts like competencies or abilities (Fareri *et al.*, 2021). Weinert (1999) describes skills, knowledge, and abilities as part of competencies, while others argue that competencies and skills are hard to separate (Oates, 2002). The Cambridge Dictionary describes *skills* as the ability to complete a task as a result of practice (Cambridge Dictionary, 2022). This definition already outlines the demarcation problem of skills: the concept is defined by a similar concept (ability). *Competencies* are often described as integrating knowledge, skills, and abilities (Weinert, 1999; Markus *et al.*, 2005). Despite ongoing discussions, a consensus has yet to be reached on the definition of competencies and the criteria that differentiate them from related concepts (Markus *et al.*, 2005). Frameworks like the Organization for Economic Cooperation and Development (OECD) (2018) or Schüller *et al.* (2019) aim to provide a comprehensive overview of the existing terms building on Databases like O*NET (U.S. Department of Labor/Employment and Training Administration, 2022) or ESCO (European Commission, 2022) which provide thousands of entries. In summary, the skill and competency definition problem is not of missing data, but rather the conceptional basis is missing, hindering a common understanding.

The definition of hard skills is primarily common sense, while the conceptualization and delineation of soft skills remain unclear (Fareri *et al.*, 2021). *Hard skills* are technical skills required to perform a task or job like programming (Hendarman & Cantner, 2018). On the contrary, there is a debate about whether soft skills are inherent or acquired. Some researchers consider *soft skills* as embedded personality traits (e.g., Deming & Kahn, 2018). Others see soft skills achievable through experience and knowledge (Mitchell *et al.*, 2010; Robles, 2012). Recently, soft skills received much attention, and due to their relevance in today's workforce, they are often referred to as 21st-century skills (Trilling & Fadel, 2009; van Laar *et al.*, 2017; OECD, 2018). Trilling and Fadel (2009) separate these skills for a digital and connected world into (1) learning and innovation skills enabling people to question facts critically and solve problems, (2) information, media, and technology skills referring to the competent use of information and communication technology (ICT), and (3) professional and life skills including cross-cultural skills, and flexibility. Similar, van Laar *et al.* (2017), who argue that 21st-century skills extend beyond digital skills and include ICT-related and non-ICT skills.

Professional requirements are evolving in response to changing job demands, with more than one-third of job ads asking for cognitive and social skills (Deming & Kahn, 2018). The shift towards more complex skills suggests rethinking professional skill requirements and their assessment (Autor *et al.*, 2003), as current assessment methods focus on hard skills (van Laar *et al.*, 2017). The practical implementation and accurate measurement pose challenges due to the complex and ambiguous nature of soft skills, compounded by their interdependencies. Considering this, a systematic and simultaneous approach to capturing diverse skills becomes indispensable, as emphasized by Unicef (2019). Given that individuals exhibit different skills (Rychen, 2016), it becomes necessary to address the distinct skills of employees during the assessment process. However, conventional face-to-face evaluations often encounter limitations regarding resource availability and personnel expertise within the work context. Consequently, the utilization of ICT for personalized assessments assumes paramount importance (CEDEFOP, 2017). As a contribution to an aggregate definition and delineation between these concepts, this paper captures the different perspectives on skills.

2.2 Automated Skill Assessment

Assessment is crucial in the corporate world. Its importance extends beyond recruitment and job suitability testing to the need for continuous learning and skills development. Therefore, the assessment includes evaluating, measuring, and reporting on individuals existing hard and soft skills and further development opportunities (Paiva *et al.*, 2022).

Assessment is at the heart of learning experiences and is crucial for shaping learners' understanding of the curriculum and their ability to progress (Hettiarachchi *et al.*, 2015). In this context, individual skills can be assessed by questionnaires, years of experience (Pektor *et al.*, 2019), or rating scales. Baartman *et al.* (2006) point out that the reliable assessment of skill acquisition is hindered as it is unclear which requirements need to be achieved. The question arises whether already established assessment criteria apply to the changed skill requirements or whether new methods or method combinations are necessary. The need for innovative professional skill assessment methods attracted the European Union's attention calling for standardized and ICT-based approaches (Redecker, 2013). Technology is vital in this process and adds value to assessment-related activities. In this regard, the digital assessment includes any web-based method that enables systematic inferences and assessments of skills, knowledge, and abilities (Guerrero-Roldán & Noguera, 2018). However, established non-digital methods are still based on subjective perception (Sander *et al.*, 2020), and automated processes can prevent potential biases and discrimination (Gerogiannis *et al.*, 2015).

Automated assessment tools have long been a research focus in computer science, particularly on programming skills. Some studies examine automatic approaches for programming skill assessment (Ala-Mutka, 2005; Souza *et al.*, 2016). However, many lack a conceptual basis (Souza *et al.*, 2016) or are already outdated (Ala-Mutka, 2005; Ihantola *et al.*, 2010). Petrov (2020) presents a new attempt by selecting expert networks based on project results with algorithms. Similarly, Bohlouli *et al.* (2017) describe competency analysis in HR information systems and use mathematical and statistical software technologies to assess competencies in HR information systems. Their framework increases the efficiency of assigning specialists to projects and simplifies the hiring process. Part of the literature refers to data mining with CVs as data sources to extract skills, like Nikitinsky (2016), who investigates the possibility of improving talent and HR management with data mining. To sum up, there is a growing interest in exploring automated assessment, which extends beyond programming to holistic features like quality, behavior, security, and novel assessment methods (Paiva *et al.*, 2022).

3 Research Approach

We followed a formal systematic literature review process by Vom Brocke *et al.* (2009) for searching and screening articles within relevant journals and conference proceedings of information systems, management studies, and education research. We used seven digital libraries, EBSCO Host, ACM Digital Library, AISeL, ScienceDirect, IEEE Xplore, ProQuest, and Web of Science, which include a substantial share of the relevant literature. The search queries were based upon key terms ((“assess *” OR “evaluat*” OR “test*”) AND (“skill*” OR “competenc*”) AND (“automat*” OR “algorithm*”)). The queries varied for the databases but were semantically equivalent. We included English articles published from 2000 to 2022 (August). The search revealed 7008 hints within the title, abstract, and keyword sections. We screened the titles and abstracts of these papers for relevance in alignment with our research question. After excluding duplicates and non-relevant publications, which did not address one of our research topics (i.e., automized assessment, algorithms for assessment, skills, competencies), we ended up with 125 publications. Next, papers dealing with automated skill assessment marginally, such as automatic feedback or grading, were removed. This led to 89 results. We then applied the inclusion criteria: (1) focus on the automatic assessment of professional skills/competencies, (2) at least semi-automatic approach, (3) approach was evaluated with and designed for adults, either in university or work context, (4) professional skills or competencies as units of analysis, (5) focus on the automatic assessment of more than one skill or competency. This resulted in 22 studies. After conducting forward and backward searches using Google Scholar, five studies were added, resulting in 27 publications for in-depth analysis. Figure 1 outlines the paper selection process. Papers were examined using an explorative coding scheme (Mayring, 2015). We coded along pre-defined categories: (1) the conceptualization and definition of skills, competencies, and related terms, as research on these needs to be more apparent (Fareri et al., 2021). Further, we focused on (2) the examined skills used for assessment, to determine if automated methods primarily emphasize hard skills, as argued by van Laar *et al.* (2017) for conventional methods, or if the assessment methods align with the growing emphasis on soft skills. (3) The applied automatic assessment approach for these skills was analyzed. The reliable and up-to-date measurement of skills places increased demands on automated methods as these must be capable of both accurately measuring data and processing it (Paiva et al., 2022). (4) The data source was included. While CVs and resumes are a known source of data for skills (Guo *et al.*, 2016; Chifu *et al.*, 2017), this representation displays one point in time and thus has limited reliability (Ikegwu et al., 2022). The first author conducted analysis and coding, which were presented to the second author for validation. Any discrepancies were resolved through discussions to ensure the consistency and validity of the results.

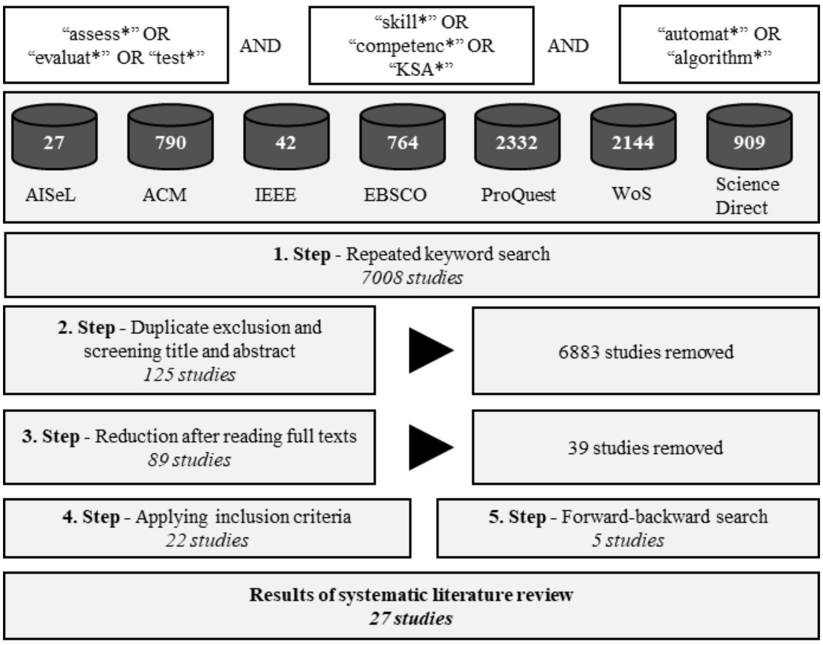

Figure 1. Literature Review Process.

4 Results

This section outlines how previous research described skills and competencies, which skills and competencies were covered and how the assessment methods were designed. Table 1 shows a concept matrix following Webster and Watson (2002) and outlines the papers' contribution to the specific categories.

The 27 included articles were published over the preceding eleven years (2011-2022), with 20 papers (71.4%) published after 2015 and four (14.8%) published in 2021 or 2022. This indicates the increasing importance and research interest. Most publications (19, 70.4%) are experimental studies on a method development and experimental evaluation. 40.7% (11) are conference papers, and 51.9 % are journal articles (14). Based on journals, papers can be assigned to IS (7, 25.9%), AI and Algorithms (5, 18.5%), Education (4, 14.8%), Engineering (2, 7.4%), and Automatic Control (2, 7.4%). However, many categories include one paper, like Expert Systems or Mathematics.

Table 1. Conceptual matrix based on Webster and Watson (2002)

	Definition		Examined Concept			Automation Approach		Data source		
Unit of Analysis	**Skill**	**Competency**	**Hard Skills**	**Soft Skills**	**Competencies**	**Extraction**	**Processing**	**Self-Assessment**	**Text**	**Behavior**
Aguinaldo (2019)	x		x	x			x	x		
Bachtadze *et al.* (2019)		x			x		x			x
Barthakur *et al.* (2022)				x			x	x		
Cepero *et al.* (2015)				x		x	x			x
Chernyshov (2016)						x				x
Chifu *et al.* (2017)			x	x		x	x		x	
Colucci *et al.* (2011)		x			x		x		x	
Duchanoy *et al.* (2020)	x		x	x			x		x	
Dzwigol *et al.* (2020)		x			x		x		x	
Fahrenbach *et al.* (2020)					x		x		x	
Fareri *et al.* (2021)	x			x		x			x	
Fauzan (2018)		x	x	x			x	x		
Gerogiannis *et al.* (2015)			x				x			
Hoang *et al.* (2018)			x	x		x	x		x	
Judrups *et al.* (2015)		x			x	x				x
Konstantinidis *et al.* (2022)			x	x		x			x	
Leontyev *et al.* (2016)		x		x			x	x		
López *et al.* (2022)					x	x	x			
Lula *et al.* (2018)		x	x	x		x	x		x	

Nikitinsky (2016)		x			x	x	x		x	
Pektor *et al.* (2019)		x	x				x		x	
Petrov (2020)		x			x		x			x
Rayón *et al.* (2014)		x			x	x	x	x		
Shadskay *et al.* (2016)		x			x	x	x	x		
Zaouga *et al.* (2019)		x					x		x	
Zhang (2022)			x	x		x				x
Zhao *et al.* (2019)	x		x	x		x	x			x

4.1 Definition of Skills and Competencies

A notable finding is the lack of consensus on the definitions of skills and competencies. As Table 1 shows, 37% (10 papers) do not define one of these concepts. Some refer to skills as a concept with an apparent definition, like Cepero *et al.* (2015). In comparison, the definition is made over operationalization measures like Barthakur *et al.* (2022), who use course learning objectives to evaluate leadership development skills, or Chernyshov (2016), who assesses professional skills by group behavior. Further studies like Chifu *et al.* (2017) or Gerogiannis *et al.* (2015) focus on extracting information from texts, e.g., by NLP or fuzzy logic, rather than dealing with the question of what skill or competency is. Other papers use previous conceptualizations of skills like the ESCO database. However, they also lack a description of how skills are seen in the database (Hoang *et al.*, 2018; Konstantinidis *et al.*, 2022). Further studies neglect a definition (Long *et al.*, 2003). López *et al.* (2022) define competencies as required by projects, e.g., documentation of requirements, without a clear delineation.

We distinguish between papers dealing with competency versus dealing with skills. Competency is the subject of interest in 13 papers (48.1%). These studies describe competency as a general term, including at least knowledge and skills (Bachtadze *et al.*, 2019; Pektor *et al.*, 2019; Petrov, 2020) or even motives (Fauzan, 2018), personal characteristics (Leontyev *et al.*, 2016; Fauzan, 2018; Lula *et al.*, 2018), self-concept values (Fauzan, 2018), attributes (Pektor *et al.*, 2019), or expertise (Petrov, 2020). Dzwigol *et al.* (2020) define competencies as comprehensive, discrete, focused, congruent, and relevant. A shared characteristic is the inclusion of behavioral measures. However, we see a disagreement about behavior being an antecedent of competency or a result. On the one hand, Bachtadze *et al.* (2019) describe competency as "the ability to perform different patterns of behavior" (p.474), Lula *et al.* (2018) define competencies as accounting for a specific behavior, and Fauzan (2018) sees behavior as an operationalization of motives, and personal characteristics. On the other hand, Zaouga *et al.* (2019) describe behavior as part of competency. Accordingly, it remains unclear if behavior constitutes competencies in the first place or results from obtaining a competency.

Few studies provide a clear statement on the definition of skills. 15 papers name skills as a unit of analysis, and four define skills. Further, skills are seen as a unit of analysis in resumes or job postings (Zhao *et al.*, 2019). The most explicit definition for skills is given by Duchanoy *et al.* (2020) as "acquired through professional experience and education, classified into industry knowledge, tools and technologies, interpersonal skills, and other skills." (p.5). The results demonstrate a significant gap between using skills as a concept for automated assessment methods and outlining what is involved in analyses. Fareri *et al.* (2021) are among the studies that address the difficulty of defining skills and establishing a conceptual basis for automated assessment, which is evident by stating that "the definition of the concept remains vague" (p.1).

4.2 Examined Skills Used for Assessment

Hard skills that are the primary object of assessment in papers of this literature review and include technical skills, e.g., being able to process and analyze data (Fauzan, 2018), and job-specific skills like IT, accounting, or logistic-related (Lula *et al.*, 2018). Lula *et al.* (2018) thereby rely on the classification of Filipowicz (2014), which assigns skills to one of four competencies: social, personal, managerial, and professional. Soft skills are dominantly described (13, 48.1%) as the unit of analysis for automated assessment (e.g., Fauzan, 2018) compared to hard skills being analyzed in 11 (40.7%) papers and competencies being the unit of analysis in 10 (37%) papers. One can see that skills are often examined while no definition of skills is given (e.g., Gerogiannis *et al.*, 2015; Chifu *et al.*, 2017; Barthakur *et al.*, 2022). Soft skills, like creative (Aguinaldo, 2019) or communication skills (Cepero *et al.*, 2015; Aguinaldo, 2019), were considered. However, the granularity varies from rather broad terms like technical or managerial competencies (e.g., Dzwigol *et al.*, 2020) over more concrete skills like communication (e.g., Aguinaldo, 2019) or problem-solving (e.g., Lula *et al.*, 2018) to detailed ones like public speaking (e.g., Rasipuram & Jayagopi, 2020) or encoding emotions (Fareri *et al.*, 2021). Examined soft skills include professionalism, loyalty, responsibility (Shadskay *et al.*, 2016), and communication (e.g., Cepero *et al.*, 2015, Fauzan, 2018). Leontyev *et al.* (2016) see activity competency as abilities for professional tasks, motivational-axiological competency as the readiness to show professional and personal competency, and integrative competency as the acquired general-cultural professional competency. Among the papers which are rather explorative in their methodology, Chernyshov (2016), Petrov (2020), Pektor *et al.* (2019), and Duchanoy *et al.* (2020) describe project-related skills. In comparison, Colucci *et al.* (2011) look for core competencies, Bachtadze *et al.* (2019) for team competencies, and Zhang (2022) takes employment skills into account. In comparison, Nikitinsky (2016) operationalizes competency by key terms for professional interest. Another group of papers relies on the conceptualization of known databases such as ESCO (Fareri *et al.*, 2021; Konstantinidis *et al.*, 2022) and O*NET or even providing their own taxonomies not described in detail (Chifu *et al.*, 2017; Hoang *et al.*, 2018; Zhao *et al.*, 2019).

4.3 Applied Automatic Assessment Approach

Within this section, we differentiate between the data extraction method and the data processing, i.e., the method of how skills or competencies were extracted from the provided data and how they were processed afterward (e.g., clustering or classifying). Because of the focus of this literature review, we will not each algorithm or tool in detail.

(1) Data extraction: In the field of competency profiling, using automated solutions for data extraction is less common. 55.6% of papers (15) use an automatic approach, while 13 (48.1%) use manual assessments like surveys or skill entries. Other studies, like Judrups *et al.* (2015), use a mix of automated and manually extracted data for competency profiling. Text mining methods are frequently employed among the papers that use automated approaches(e.g., Fahrenbach *et al.*, 2020; Fareri *et al.*, 2021; Konstantinidis *et al.*, 2022). This involves extracting key terms from textual sources. One example is the named entity normalization to extract semantic entities (e.g., Hoang *et al.*, 2018). NLP, namely the Latent Dirichlet Allocation (LDA), an algorithmic method, is used to identify semantic components from document texts like personnel profiles, CVs, or resumes (Lula *et al.*, 2018). The LDA method acts as a filter, reducing information noise in the input data. Cepero *et al.* (2015) describe a system to extract human behaviors using a multi-modal analysis, which relies on pre-defined behavioral indicators to extract features of oral communication skills with technologies such as audio or face tracking systems. An end-to-end solution for the identification of skills is provided by Konstantinidis *et al.* (2022). They describe an unsupervised, i.e., without a human-annotated database, method for skill extraction. The method consists of a semantic similarity search based on text embeddings.

(2) Data processing: Algorithms for assessment are increasing, especially in the papers after 2015. For example, Aguinaldo (2019) applied a classification algorithm to the datasets to predict the outcome of a programming course. This classifying algorithm produced a decision list with rules such as a student with good communication skills will likely pass a class. Barthakur *et al.* (2022) use NLP and, first, manually code exemplar responses to extract linguistic features. Then they apply a random forest classifier algorithm to the training dataset. They created a system that can predict the reflection level of answers on leadership concepts. Hoang *et al.* (2018) use the named entity normalization system to develop a tagging system that examines the identified skills' correct meaning. These functions contribute to a skill taxonomy. Leontyev *et al.* (2016) use an algorithm as a qualimetric assessment approach to evaluate vocational training outcomes. Other approaches build on the extraction work of the LDA, and a classification model maps the retrieved components to specific classes of skills or competencies, such as managerial skills (Lula *et al.*, 2018). Gerogiannis *et al.* (2015) take a slightly different approach and refer to a group-based fuzzy multi-criteria method. Liao *et al.* (2007) aim to evaluate and select professionals for software development tasks in line with the needed competencies and skills. López *et al.* (2022) combine a probabilistic Bayesian model with a trust graph for task grading. In comparison, Bachtadze *et al.* (2019) developed a model that is able to characterize skills, compare them to each other, calculate the cost of competence development, and determine the suitability of the individual's competence to task goals.

4.4 Data Sources

The data sources for automated assessments can be assigned into three groups. Firstly, traditional methods, i.e., not automated, such as questionnaires (Leontyev *et al.*, 2016; Shadskay *et al.*, 2016; Fauzan, 2018), self-or assessments (Leontyev *et al.*, 2016; Shadskay *et al.*, 2016) or a combination of both (e.g., Aguinaldo, 2019; Barthakur *et al.*, 2022). The second group includes textual data such as personnel profiles (Colucci *et al.*, 2011; Konstantinidis *et al.*, 2022), like LinkedIn (Duchanoy *et al.*, 2020; Fahrenbach *et al.*, 2020), resumes or CVs (Chifu *et al.*, 2017; Hoang *et al.*, 2018; Zhao *et al.*, 2019) or job advertisements (Lula *et al.*, 2018; Pektor *et al.*, 2019). The third group encompasses other sources, like behavioral data (Judrups *et al.*, 2015), 360-degree evaluations, work performance data, and interviews. Studies like Petrov (2020) and Bachtadze *et al.* (2019) describe project data used for assessment. Dzwigol *et al.* (2020) use employee data such as experience in years, educational positions, and goal achievements. Rayón *et al.* (2014) use educational data inserted by students. Interestingly, Chernyshov (2016) uses eye-tracking data for attention behavior. López *et al.* (2022) simulated data from peer assessments. Cepero *et al.* (2015) utilized facial and pose recognition features to evaluate nonverbal communication elements in presentations.

5 Future Research Avenues

Assessing professional skills or competencies via automated measures is an important antecedent to equip professionals with the knowledge of their strengths and possible development paths. Further, it provides organizations with the needed reliability and objectivity to gain an overview of the skills of their employees. This systematic review aimed to investigate the state-of-the-art regarding automized skill assessment of employees in organizations. We analyzed extant research and provided an overview of four aspects of automated assessment: the general definition of skill and competency, the examined skills in the paper, the automated assessment method, and the data sources. The meaning of our results and significant implications for future research avenues are discussed below.

The reviewed papers exhibit a significant gap between claiming to analyze skills and defining what those skills are. Over one-third of the papers reviewed do not directly address the definition of skills or competencies for their automated assessment methods. Papers like Duchanoy *et al.* (2020) broadly group them into hard and soft skills but do not refer to inclusion or exclusion criteria. Nevertheless, without a precise definition, assessment relies on individual perception of what is seen as skills and what is written in CVs or resumes. Thus, a conceptual framework on skills in automatic assessment is needed to provide a reliable data basis. Using a design science research approach could answer how dimensions and characteristics of skills can be classified from an assessment-based perspective. The examined skills reflect a wide range of possible applications. The increased focus on soft skills confirms the increasing importance (Geisinger, 2016). The fact that communication is named often, sheds light on the fundamental importance of this skill also in relation to other skills like leadership (Keil *et al.*, 2013) and strengthens the impression that skills are hierarchically structured and based on each other. Many papers do not specify which skills are part of their assessment, which could implicate that the presented methods may lack generalizability or that they assess behaviors that cannot be directly linked to specific skills. Among the methods used, most rely on NLP or an algorithmic method. These approaches enabled the development of automated assessment methods. However, the focus is still on skill data processing rather than extracting skills or competencies. This is perhaps due to the pre-existing processes in the field of skills assessment which still refer to questionnaires and self-evaluations such as psychometric tests and interviews (Hamza *et al.*, 2021).

A recent increase in interest in automated skill assessment can be observed. Among the papers, we recognize a promising development toward a reliable assessment of skills. This will be ensured by a holistic assessment of professional skills from multiple sources rather than a view limited to one source like a CV or a recruiting questionnaire. Research streams are becoming more diversified. This is primarily due to the extension of the application contexts for automatic skill assessment. Whereas earlier publications concentrated on more easily quantifiable skills like programming, they now increasingly look at more elusive soft skills like empathy or problem-solving. However, this also requires a multi-source analysis since a single aspect cannot describe soft skills. The appropriate operationalization and underlying methodologies could be very different for each skill. Future research may consider combining soft skills with interdisciplinary approaches to extend the scope of automated skill assessment. A potential research inquiry is to explore the operationalization of soft skills, such as complex problem solving, for a dependable automated assessment database. Furthermore, soft skills are often still assessed by questionnaires and self-assessment measures, which are not automatically extracted from the original source. The emphasis on automatic processes lies in the data processing phases, specifically clustering, and classification. Apart from questionnaires, personnel profiles like LinkedIn are a convenient data source, but their reliability and objectivity are limited. Accordingly, methods to automatically retrieve data from multiple sources, like team or supervisor feedback, need to be explored.

Lastly, when exploring the application contexts for automized professional skill assessment, along with HR Processes like employee development, staffing processes within projects can be interesting. Like employee development decisions, staffing processes rely on subjective assessments (McCray et al., 2002; Sander et al., 2020) and require much working time from HR professionals (Gorlov et al., 2015). An automated process suggests possible development paths for employees or estimates which employees can work on what project (Furini et al., 2022).

6 Conclusion: Contribution to Theory and Practice

Accurate measurement of employee skills is crucial in the ever-changing world of work, necessitating an understanding of underlying concepts, methods, and designs. This systematic literature review provides an overview of automated assessment methods for professional skills, revealing that most methods rely on NLP mechanisms. However, defining and operationalizing skills fall behind, and critical reflection of the data basis is missing, which hinders the establishment of a reliable basis for automated skill assessment. Overall, the results provide a deeper insight into how skill assessment can be automated and which underlying definitions and conceptualizations are used. A substantial body of literature exists about assessing skills and competencies, with the participation of diverse academic disciplines lacking a comprehensive overview. Consequently, our scholarly contribution aims to undertake a systematic review and conceptualize the extant literature, bridging the existing gaps and providing a synthesized understanding. Furthermore, this review identifies potential avenues for future research exploration, enriching the academic discourse in this field. By answering the question *"What is the state-of-the-art regarding automized skill assessment of professionals and what future research avenues can be identified?"* we contribute to the literature by providing a concise knowledge base for future research by summarizing existing methods of automated skill assessment for professionals and providing guidance for practitioners on reliable assessment, which can empower employees to develop skills independently. By synthesizing diverse perspectives and critically analyzing existing literature, we derive insights and formulate potential research avenues that address research gaps, laying the groundwork for advancing knowledge in the field. Further, automated skill assessment presents practical advantages across diverse domains. It can enhance efficiency in HR or project staffing by significantly reducing the time and effort required to evaluate individuals' skills. Standardization can be achieved by implementing predefined criteria and algorithms, mitigating subjective biases by, e.g., recruiters, and ensuring greater reliability in skill evaluations. Scalability is facilitated, allowing for the simultaneous assessment of numerous individuals, which is particularly advantageous in educational institutions, recruitment processes, and corporate training programs. Moreover, automated skill assessment enables personalized feedback and recommendations tailored to individuals' performance, empowering targeted skill development plans that address specific strengths and weaknesses.

The following limitations should be noted. First, the selection and analysis process is based on the authors' subjective decisions, which can influence the results. Second, the systematic review attempted to cover skills in general, using a broad search strategy, but this search was limited to scientific databases. Accordingly, we cannot rule out the possibility of missing relevant papers. Third, we did not assess the methodological and overall quality of included articles, resulting in a less comprehensive review.

7 References

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