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TRANSFERRING DIGITAL TWIN TECHNOLOGY ON EMPLOYEE SKILLS: A FRAMEWORK TO SUPPORT HUMAN RESOURCES

ABSTRACT

Skill assessment has become increasingly important in recent years. The shortage of skilled workers has demonstrated the need to identify suitable candidates for jobs and to develop existing employees. However, human resources processes rely on resumes, references, or job certifications to assess their employees' skills. A few years ago, the concept of a digital twin was introduced, which is a digital replica of a physical entity. While using blockchain, the digital twin technology offers tremendous potential for transfer to other contexts. In the context of these considerations, we present a framework that allows the technology of the digital twin to be combined with that of skill assessment to create an enhanced skill profile. With a job market signaling perspective, we integrate knowledge about skills, clarify the opportunities of assessment, and develop a framework for a digital skill twin. In doing so, we argue that the multi-source and multi-method approach of such a digital skill twin leads to increased validity, reliability, and standardization. We thereby contribute to theory and practice by developing a new framework that offers employees to know their strengths and development potential and organizations to assess their employees' skills.

Keywords:

Digital Twin, Skill Assessment, Skill Profiles, Human Resources

1 INTRODUCTION

A growing number of research studies predict that globalization, technological developments, and demographic trends will reshape our labor markets (Djumalieva & Sleeman, 2018; OECD, 2018). According to a World Economic Forum report, 50% of all workers will need to be reskilled by 2025 as the use of technology increases (Whiting, 2020). Other numbers predict a 40% change in skills for the same jobs (LinkedIn, 2022). As these numbers demonstrate, technological change affects the required activities of employees in many ways, for example, by involving employees as stakeholders in technology development and implementation and by changing the scope of decision-making for employees (Myers, Steffen, & Waldman-Brown, 2021). According to Bakhshi, Downing, Osbrone, and Schneider (2017), there will also be a shift in focus toward interpersonal, higher-order cognitive, and systems skills. In addition, structural changes such as work shift to freelancers and online labor platforms (e.g., Upwork) are transforming work, thus requiring adapted digital processes from Human Resources (HR) (Möhlmann, Zalmanson, Henfridsson, & Gregory, 2021). As a consequence, it is time to rethink the current human resources processes, which today are based on subjective decisions and can no longer cope with the information age. The digital twin solution presented within this paper offers the chance to enhance human resources processes like hiring and re- and upskilling significantly by capturing data on employee skills and providing analysis and predictions.

To date, the assessment of job skills has been based on rather subjective statements, either by the person himself or by third persons evaluating the skills of another person, such as supervisors or teammates (Judrups, Zandbergs, & Kazakovs, 2015). The basis for these evaluations are often subjective impressions (e.g., sympathy) or single output variables, such as task or project performance (Judrups et al., 2015; Petrov, 2020). This created several challenges for employees as well as for employers. Employees cannot rely upon certainty on their skills statements to decide on future career development, and employers face a considerable information asymmetry as they also lack certainty as to whether the information provided by candidates in the recruiting process, for example, is reliable. Clarifying this uncertainty is time-consuming and labor-intensive for candidates and HR professionals (Gorlov, Lazareva, & Fursov, 2015). However, it does not provide the necessary reliability, validity, and objectivity, meaning independence from influences on the results (Sander, van Dellen, Hartmann, Burger-Kloser, & Keller, 2020). Research conducted by Rayón, Guenaga, and Núñez (2014) contends that skill assessment consists of four significant challenges: The first is a lack of scalability or the difficulty of transfer; the second is the subjective nature of interpretation by raters, such as supervisors; the third is the difficulty of finding latent capabilities behind activities or operationalizing capabilities; and the fourth is a lack of appropriate and applicable assessment methods. These challenges can manifest in systematic dilemmas like selection bias and discrimination (Amis, Mair, & Munir, 2020). As demonstrated, assessing skills required for the 21st century is difficult, especially for companies. Companies require more consistent standards and trustworthy procedures for measuring skills (Judrups et al., 2015). Against this backdrop, new techniques need to be considered to support hiring processes and employee professional growth. However, the diversity of new skills demands new assessment methods that capture more prosperous and complicated skills (Rayón et al., 2014). On the one hand, this implies that adequate assessment methods that provide a valid basis for skills must be implemented. On the other hand, an appropriate form of representation that maps skills to fit the needs of both employers and employees must be established.

The ubiquitous availability of data and the development of algorithms make it possible to gain new and more comprehensive insights into skills. In particular, methods such as natural language processing (NLP) and algorithmic work improvement have proven helpful for a variety of applications in labor market studies (Kellogg, Valentine, & Christin, 2020)Fareri, Fantoni, Chiarello, Coli, & Binda, 2020). In this paper, we explore the transferability of the digital twin solution to use these advancements for human resource processes. The starting point for our assumptions lies in creating a virtual depiction of a person's skills and expertise (Zhao, Cao, Xiao, Zhu, & Cheng, 2019). It contains a complete and comprehensive set of data regarding a person's skills, qualifications, and experiences, along with information about their performance and accomplishments in those areas (Furini et al., 2022). We argue that a digital skill twin differs from a traditional skill profile because it is based on verifiable data instead of subjective data. Based on the premise that this information can be gathered and confirmed from various sources, including educational institutions, employers, and certification organizations, a digital skill twin is more likely than a traditional skill profile to be accurate and reliable (Furini et al., 2022). Following the job market signaling perspective presented by Spence (1978), we argue that a digital skill twin can support the process of recruiting and hiring, learning and development, and career management. On the one hand, they provide a detailed and objective view of an individual's skills, assisting organizations in finding and hiring the proper candidates and reducing their uncertain investment. On the other hand, candidates can secure the signals in their application, making them temper-proof. Accordingly, a signaling equilibrium is created, reducing the probability for the employer to receive unexpected information after hiring and increasing the outcome of the hiring process (e.g., higher wages). Further, individuals can better understand and enhance their own skills. Accordingly, we aim to analyze what aspects characterize the digital twin technology and how this phenomenon could be applied to human resources. We address the following research question: *What features need to be considered when developing a digital twin for employee skills?*

We develop a framework that outlines the prerequisites and boundaries of a digital skill twin and discuss how this technology may evolve in the future. This technology presents a toolset for management researchers and business practitioners. It contributes to research and practice by providing navigation through the diverse skills landscape by identifying this technology's main characteristics and relevant skills dimensions. To achieve this, we bring together research from different management disciplines, including Human Resources, Information Systems, Business Research, Learning Strategies, and Ethics. We consolidate the extant empirical results on skill acquisition and conceptualization and develop specific relevant research questions. Our framework explains the novel phenomenon of a digital skill twin.

1 CONCEPTUAL BACKGROUND

This section offers an overview of the central concepts that are part of the digital skill twin. We first outline the digital twin technology and where it originates from. Secondly, we discuss the term skill and describe its meanings focusing on today’s essential 21st-century skills. Lastly, the characteristics of skill profiles are delineated while pointing out the flaws of existing skill profile approaches.

1.1 Digital Twin Technology

Initially from industry, Michael Grieves presented the concept of a digital twin in 2003 (Grieves, 2014), and NASA revealed it to the public for the first time in 2012 (Glaessgen & Stargel, 2012). Digital twins are digitized representations of physical objects, connecting the physical and digital worlds (Zhao et al., 2019). According to Hartmann and van der Auweraer (2021), digital twins incorporate all (electronic) information and knowledge generated over a product’s lifecycle, from product definition and idea until the end of its existence. For example, this information can comprise design drawings, technical models, or analysis (Hartmann & van der Auweraer, 2021). As a result, they act as a connection between the virtual and real worlds, with the intention of modeling, comprehending, forecasting, and optimizing the corresponding actual values (Enders & Hoßbach, 2019). This is accomplished through the use of simulation and/or data-driven methodologies (Graessler & Poehler, 2017). Thus, digital twins are a significant tool for understanding and modeling performance, predicting behavior, and optimizing operations and services (Graessler & Poehler, 2017).

Digital twins are viewed as a significant development by the economy and research. For example, it has been in the top 10 strategic technology trends for 2017, 2018, and 2019 (Kerremans, Burke, Cearley, Velosa, & Walker, 2019). Hartmann and van der Auweraer (2021) claim their high potential for savings and, at the same time, enabling new opportunities for employee skills and employee-task matching. Similarly, Saracco (2018) argues that digital twins and AI offer the highest innovation potential for future work design. However, digital twin technology has been put to use in a wide range of industries. According to Enders and Hoßbach (2019) examination of the literature, particularly in manufacturing, aerospace, the energy sector, automotive, and shipping. However, physical products have always been virtualized, and only Graessler and Poehler (2017; 2018) apply the concept of a digital twin to represent people (workers) within a production system. The authors refer to machine-specific skills, preferences, and schedules stored in the digital twin. They use the digital twin to enable people to participate in computer-aided decision-making and to communicate their preferences for production schedules (Graessler & Poehler, 2018). However, they relate the functionality of this twin to the production context, neglecting the enormous potential of this idea for human resources.

1.2 Definition of Skills

Although the notion of skills has been the subject of extensive research for nearly 100 years (e.g., Seashore, 1930), the conceptualization of skills remains fuzzy (Fareri, Melluso, Chiarello, & Fantoni, 2021). This is related to the difficulty delineating related concepts such as competencies or skills. For example, Weinert, Franz, E. (1999) describes skills, knowledge, and abilities as part of competencies, while others, such as Oates (2002), argue that competencies and skills are hard to separate. The Cambridge Dictionary (2022) describes skills as “ability to do an activity or work well, mainly because one has practiced it”. Marrelli, Tondora, and Hoge (2005) distinguish skills and abilities based on the outcome to be achieved. They describe skills as a demonstrated cognitive or physical ability to successfully perform a task with a wide range of possible outcomes. At the same time, skills are the ability to perform mental or physical tasks with a specific outcome. A more precise delineation is that skills are learnable abilities, whereas abilities refer to temporally stable characteristics inherent in a person (Torrence, Nelson, Thomas, Nesmith, & Williams, 2021). In this paper, we will refer to skills in the sense of Torrence et al. (2021) and specialize in learnable skills. Despite different definitions, it is common knowledge that individual skills vary and that each person has strengths and weaknesses in different areas (Rychen, 2016).

There are some relevant aspects to consider as we delve into the concept of skills. While the distinction in hard skills is primarily common sense, the clear delineation of soft skills and their conceptualization remains vague (Fareri et al., 2021). Hard skills, such as programming in Java, are seen as technical skills required to perform a task or job (Hendarman & Cantner, 2018). In comparison, there are different views of soft skills and whether they are innate or acquired. On the one hand, researchers consider soft skills a collection of embedded personality traits (Deming & Kahn, 2018), thus innate rather than acquired. On the other hand, soft skills are viewed as a holistic concept that can be acquired through experience and knowledge (Mitchell, Skinner, & White, 2010; Robles, 2012). Moreover, the operationalization of soft skills is much more complex than hard skills (Yan et al., 2019). For example, while a test can determine a person's reading skills, and it is obvious what this means, complex problem-solving is challenging to capture in a single test, and understanding this skill is not so clear. The ambiguity and difficulty associated with understanding soft skills are already evident here. Nevertheless, these skills are becoming increasingly relevant today to equip workers to deal with technological changes within the workplace (Geisinger, 2016).

1.3 Key Features of 21st-Century Skills

It is undeniable that professional requirements are changing in organizations. For instance, cognitive skills are required in 37% of job advertisements, while soft skills are required in 36% (Deming & Kahn, 2018). Compared to the past, artificial intelligence is now able to perform many routine tasks independently, for example, but is not able to identify innovation or creativity potential (OECD, 2018). Similarly, employers expect critical thinking and problem-solving to gain importance over the next years (Whiting, 2020). Further, self-management skills such as active learning, resilience, stress tolerance, and adaptability are emerging (Whiting, 2020). In line with this trend, employers face difficulties finding suitable candidates for the changing job requirements (e.g., Horrigan, Heggeness, Bahn, & Strain, 2022; Sumption, 2022). Consequently, there is a growing reliance on internal training and development (LinkedIn, 2022; ManpowerGroup, 2017), and a reconsideration of occupational skill requirements and the way they are captured is required to reflect more sophisticated worker skills (LinkedIn, 2022). Following this perspective, these soft skills have received much attention and are often referred to as decisive 21st-century skills (Aguinaldo, 2019; Geisinger, 2016; OECD, 2018; Trilling & Fadel, 2009). Trilling and Fadel (2009) argue for three critical skill sets in a digital and connected world. First, *learning and innovation skills* enable people to question facts critically, solve problems, communicate and collaborate, and develop creative and innovative solutions. Furthermore, *information, media, and technology skills* refer to the competent use of media and Information and Communication Technology (ICT). Finally, *professional and life skills*, including intercultural competence, productivity, and flexibility. A study by the OECD (Ananiadou & Claro, 2009) outlines three similar dimensions of 21st-century skills. First is the dimension of *information*, distinguishing between information as a source, which requires the skills of search, selection, evaluation, and organization, and information as a product, where the restructuring and modeling of information and development of own ideas are essential. Second is *communication* with subdimensions of collaboration, virtual interaction, and effective communication. Third is *ethics and social impact,* with the sub-dimensions of social responsibility and social impact. In comparison, the National Research Council, the Partnership for 21st-century skills, and the National Science Teachers Association emphasize the following 21st-century skills (Geisinger, 2016): *Basic subject knowledge,* which means that regardless of individual expertise, a thorough comprehension of science content and the essence of science is vital. Next, flexibility, adaptability, and creativity are required for managing uncertain, fast-changing tasks, technology, and working situations. *Critical thinking, creativity, and non-routine problem-solving* are necessary, as learning is about creatively developing and applying critical thinking. *Communication, collaboration, social, and intercultural abilities* are all required to be able to work in teams and to collaborate effectively.

Given the lack of standard definitions and agreement on a specific set of 21st-century skills and competencies, it was decided to adopt as comprehensive a definition and list of such skills as possible, based on the conceptual frameworks described above and ensuring that skills from the commonly mentioned dimensions **-** *information and technology*, *communication and collaboration*, and *critical thinking and problem-solving* **-** are covered.

1.4 Characteristics of Skill Profiles

A *skill profile* is a written or electronic record that describes a person's skills and experience. It often includes a list of the individual's unique skills and abilities and information on their experience, education, and training. A skill profile can be advantageous for many reasons, for instance, providing a clear picture of a person's skills and qualifications to potential employers or clients, detecting skill gaps, and developing relevant training (Traynor, Wellens, & Krishnamoorthy, 2021). Furthermore, offering a compiled account of one's skills enables the individual to prioritize development and improvement while giving a reference point for progress and performance evaluation (Paiva, Leal, & Figueira, 2022). A skill profile can be developed by the individual or a third party, such as a manager or recruiter. It can be presented in either textual or graphic form, such as a list or graph, and it can be updated regularly to reflect changes in a person's skills and expertise.

Assessment is clearly tied to skill profiles. It has also become almost indispensable in the corporate world. For example, assessment centers are used worldwide for development, diagnostic, and selection purposes (Kleinmann & Ingold, 2019). However, assessment is not limited to this application context. It is also vital to document the status quo of employees' skills in order to provide employees with lifelong learning. A traditional assessment comprises processes such as analyzing, measuring, and reporting on communication, metacognitive skills, and the person's future development potential (Paiva et al., 2022). Baartman, Bastiaens, Kirschner, and van der Vleuten (2006) point out that when appropriate assessment methods are developed, reliable assessment of skill acquisition is hindered by the fact that it is unclear what requirements need to be met for different skills. The question arises whether already established assessment criteria are applicable to the changing skill requirements or whether new methods or combinations of methods need to be used. However, the development of appropriate assessment methods is critical because it is on this basis that decisions are made about what is learned and promoted. This effect, known as "washback" or "backwash", means that learning activities focus on what is being measured (Alderson & Wall, 1993). Thus, assessment is the most important learning stimulus (Baartman et al., 2006).

Social media platforms such as LinkedIn have been one of the most important breakthroughs in personnel selection and recruitment in recent years (Roulin & Levashina, 2019). Companies regularly look at candidates' social media presence before making initial hiring selections (van Iddekinge, Lanivich, Roth, & Junco, 2016). In this context, it can be assumed that social media profiles allow companies to learn more about candidates' personalities, skills, experiences, and values and to assess how well candidates' qualifications match job requirements or company culture (Bangerter, Roulin, & König, 2012). In the following, we use LinkedIn as an example of a digital skills profile because it is a social media platform explicitly designed for use in a work context (Weidner, O'Brien, & Wynne, 2016). Accordingly, candidates' LinkedIn profiles contain much job-related information. They add information about their education, work experiences, projects, volunteer or association activities, and computer programs in which they are proficient (Shields & Levashina, 2016). Consequently, LinkedIn profiles serve as extended online resumes and contain much skill-related data (Kluemper, Mitra, & Wang, 2016).

In recruitment and selection research, there are a variety of criteria for evaluating and examining the potential value of different selection processes (e.g., Noe, Hollenbeck, Gerhart, & Wright, 2006), while the most commonly cited criteria are reliability, validity, legality (i.e., potential negative impact), and standardization (Roulin & Levashina, 2019). Yet, social networking platforms such as LinkedIn are often used to make selection decisions without verifying that such a method meets accepted selection standards (Roulin & Levashina, 2019). This means that evaluating skills in commonly used skills profiles such as LinkedIn relies on subjective criteria and opinions, making them vulnerable to bias (Yan et al., 2019). Because skills can be self-reported on LinkedIn, they may not be independently verified or validated. For example, a skills profile might include teamwork as a skill for an individual. However, there is no mechanism to ensure that this is accurate, therefore valid and not just something a person writes in their profile because recruiters are looking for it. LinkedIn tries to prevent this partly by using a verification option that allows endorsing other users' self-reported skills (LinkedIn, 2023). But here, too, the question arises as to whether other users can assess the skills, which diminishes the validity and reliability of these statements. As a result, the accuracy and reliability of skills profiles are at least questionable, as they may not provide a complete or objective picture of a person's skills. Another potential problem with existing skill profiles is that they may be difficult to compare, and individual skills may be difficult to standardize (Roulin & Levashina, 2019). Different competency profiles may use different terms, categories, and definitions to represent the same competencies, making it difficult to accurately compare the skills of different individuals.

To sum up, these problems can make it difficult for organizations to assess the skills of potential candidates accurately and can limit the effectiveness of skills-based recruiting and hiring practices.

2 A FRAMEWORK FOR THE TRANSFER OF THE DIGITAL TWIN TECHNOLOGY ON EMPLOYEE SKILLS

2.1 The Digital Skill Twin Technology

In the following section, we present a framework that describes how digital twin technology can be applied to the skills domain. We build on the work of Furini et al. (2022), who describe how digital twins can be used in education to create personalized learning models. We want to use this technology similarly but develop reliable, tamper-proof, decentralized skill profiles for employees and companies. The digital twin technology has high innovation potential for human resources and the future of work, firstly by providing a trustworthy data basis for sound and data-driven decisions, and secondly by making predictions about further development paths or the suitability of different employees or candidates for different jobs. We will first describe the idea of the digital skill twin by building on the effects of the digital twin technology described above. We then present five assumptions that we believe are essential for realizing a digital skill twin in human resources.

A digital skill twin is a digital representation of a person’s skills and knowledge. It typically contains detailed and comprehensive data about a person’s skills, qualifications, and experience. A digital skill twin differs from a traditional skill profile because it is based on objective data rather than subjective opinions. This data is collected and verified through a variety of sources, including educational institutions, employers, and certification bodies. As a result, a digital skill twin is more accurate and comprehensive than a traditional skill profile. Digital twins integrate all (electronic) information and knowledge by combining data from multiple sources (Furini et al., 2022). This enriched skill profile is ideally created throughout the learning period, from training to working life (Glaessgen & Stargel, 2012). They provide the ability to capture and maintain data electronically, continuously, and virtually (Enders & Hoßbach, 2019). For example, a digital skill twin can include data about an employee's academic background and previous work at other companies. The database enables each employee to map their skills as comprehensively as possible.

Digital skill twins can be useful in various human resources-related contexts, including recruitment and hiring, learning and development, and career management. They provide a detailed and objective view of an individual's skills, which can help organizations identify and hire suitable candidates and enable individuals to better understand and develop their own skills. Digital twins provide a solution to training and automation needs by combining detailed insights into individuals' skills, predictions of potential employee development paths, and the assignment of employees to tasks. In addition, algorithms can analyze the twin and create training or materials for improvement (Enders & Hoßbach, 2019). Digital twin analysis can thus provide important input and predictions (Liu, Fang, Dong, & Xu, 2021). Such analysis can give people a reliable assessment of their strengths and developmental potential.

2.2 Assumptions for the Digital Skill Twin Framework

Within this section, we will outline five different assumptions that are central to consider for our framework. They provide guidance for transferring the digital twin technology in the domain of employee skills in order to provide a reliable data-based solution.

Layered representation

Several layers are required to implement such a digital twin for employees practically. The *data layer* must include intelligent strategies for creating the employee's digital twin (using on-site, online, and offline activities, such as CV information, work samples, project results, and training) and intelligent algorithms for analyzing digital twins and personalizing skill development and acquisition (Furini et al., 2022). The *technology layer* involves the blockchain as the only logical technical implementation. With this, the information can be mapped in a tamper-proof and, above all, transparent manner. Both companies and employees can make entries that are then objectively tested for accuracy. The decentralized administration offers another advantage of this solution. The data belongs to the employees and is not managed by third parties; it can be retained even if the employee changes employer. Lastly, a *presentation layer* must include an accessible and personalized interface. However, this paper will focus on the data and technology layer as these constitute the basis for the digital skill twin (Assumption 1).

Underlying Skill Taxonomie

To map the 21st-century skills, namely information and technology, communication and collaboration, and critical thinking and problem-solving, in a digital skill twin, a hierarchical breakdown of the individual skills into their aspects and operationalization options is required. Accordingly, it is possible to draw on existing literature on skill taxonomies to construct the data layer. For example, the Organisation for Economic Co-operation and Development (OECD, 2018) and Schüller, Busch, and Hindinger (2019) have attempted to provide a comprehensive overview of the extensive concepts that exist in research. Databases such as O*NET (The Occupational Information Network) (U.S. Department of Labor/Employment and Training Administration, 2022) or ESCO (European Skills, Competences, Qualifications, and Occupations) (European Commission, 2022) approach the topic of skills and offer thousands of entries. Nevertheless, this assumption indicates that a data-based framework construction on individual skills is necessary to lay an accurate picture and a solid conceptual foundation for further steps (Assumption 2).

Multi-source Approach

It is inevitable to use a multi-source approach to ensure the added value of detailed insight into competencies and higher reliability. Accordingly, data on work on projects, study activities, and qualifications can and should be included. This data - for example, what language courses the employee has taken - is an essential part of an employee's digital twin and can be captured automatically using various technologies. For example, data such as academic background can be extracted from documents such as resumes using natural language processing. Work on projects (e.g., collaboration, reliability, and tasks completed) could be accessed through feedback from supervisors and colleagues (e.g., via 360° feedback). At the same time, for cognitive skills, data from aptitude diagnostics can be used for personnel selection (Assumption 3).

Multi-method Approach

Multiple assessment methods are required to capture relevant skills. However, measuring skills is complicated due to the variety of skills already mentioned above. Soft skills make up a large part of 21st-century skills but are challenging to capture (Botke, Jansen, Khapova, & Tims, 2017). For example, the ability to solve complex problems is difficult to demonstrate through a credential. On the contrary, this skill requires assessment of work outcomes. Many skills cannot be adequately captured by single tests or assessment methods but require a combination of, for example, life history facts, psychometric tests, behavioral assessments, and task-related outcomes. Therefore, it is necessary to capture skills using more than one method and to capture and map them digitally (Baartman et al., 2006). However, a multi-method approach generates vast data, so at least part of the skills assessment needs to be automated. Automated assessment methods include both the process of data extraction and the process of data processing and can be done, for example, by using NLP techniques such as text mining. Here, relevant text parts are automatically extracted from a given document, such as a resume or a certificate of employment. One example of this technique is given by Nikitinsky (2016), who explores the possibility of using data mining to improve talent and human resource management. The article also describes a mechanism that analyzes employees' documents to extract their skills (Assumption 4).

Realization via Blockchain

The main idea of creating digital twins is to construct a virtual representation of physical entities in the digital space to monitor, for instance, its value creation process, predict maintenance, and make products tamper-proof. To achieve this, the technology layer requests a blockchain approach that already allows realizing the idea of digital twins in production contexts, health care, quality management, and many more areas of application (Liu et al., 2021). The technical implementation of our digital skill twin will be achieved through the blockchain to allow a decentralized, temper-proof solution (Assumption 5).

As displayed in Figure 1, the technology layer constitutes the blockchain approach. In contrast, the data layer is comprised of the skill taxonomy, the multi-source, and the multi-method approach, which altogether represent our digital skill twin framework.

Insert Figure 1 about here

2.3 The Blockchain as a Technological Solution

Originating from Bitcoin, a blockchain allows the completion of decentralized transactions in a peer-to-peer network (Esmat, Vos, Ghiassi-Farrokhfal, Palensky, & Epema, 2021). This eliminates the need for mediators that must be trusted by contracting parties redundant and allows immutable, transparent, authentic, decentralized, and distributed transactions (Monrat, Schelen, & Andersson, 2019). Next to completing transactions (such as Bitcoin), blockchains allow sharing and synchronizing information. In manufacturing, for instance, customers can follow every step of the value-creation process (Raj, 2021).

A blockchain is a decentralized and distributed ledger with a chain network of blocks recording historical transactions and activities (Jo, Hu, Yu, Sun, Conti, & Du, 2020). A transaction (or uploading information) can be described as a record of actions (Ismailisufi, Popovic, Gligoric, Radonjic, & Sandi, 2020; Jo et al., 2020). These transactions happen inside blocks of the blockchain. A consensus mechanism is implemented to ensure that the information stored on the blockchain is real (Lashkari & Musilek, 2021). The mechanism is based on a resource-demanding, hard-to-solve, and easy-to-verify cryptographic puzzle, a so-called "proof-of-work" concept (Ismailisufi et al., 2020). Miners aim to solve this puzzle and get remunerated as soon as it is solved (Gervais, Karame, Wüst, Glykantzis, Ritzdorf, & Capkun, 2016). The higher the possible remuneration, the faster miners solve the puzzle and prove the information in blocks (Gervais et al., 2016). To ensure immutability in the blockchain structure, each block contains the previous block's hash and can readily detect tampering with a block and transactions (Gervais et al., 2016). In case a block with varying information is detected, it is not added to the chain; information and transactions are not stored or completed, and all members of the chain are informed about the information discrepancy between blocks (Lashkari & Musilek, 2021).

A blockchain is a composition of individual blocks (Singh & Singh, 2016). Every block contains (1) information about a certain number of transactions, (product) information or document, (2) a reference to the preceding block in the blockchain, and (3) the answer to a hard-to-solve and easy-to-validate mathematical puzzle (Bonneau, 2019). To secure that information uploaded to the block is unmodified, a copy of the whole chain is stored on every computer in the network (so-called nodes) and is synchronized regularly, which ensures the de-centrality of the system. A new block of data will only be added to the chain if all computers on the network reach a consensus that the data (transaction, documents, etc.) are valid (Wright & Filippi, 2015). The content of each block is stored in a Patricia-Merkle-Tree (MPT). The MPT is a fundamental structure used to store data in the blockchain and offers a tamper-proof and optimized data structure (Heshmati, Bayat, Doostari, & Pournaghi, 2022).

Blockchains are categorized into two types, public and private blockchains (Hao, Li, Dong, Fang, & Chen, 2018). Compared to a public blockchain described above, a private blockchain's governance model is designed to be more centralized. This means that not everyone can read, write, or audit the data on the blockchain (Ismailisufi et al., 2020). Instead, a private blockchain is controlled by an organization or a group (Paillisse et al., 2019). This group or organization decides who is allowed to read, write, or audit information stored on the blockchain. Updates and changes in the source code need to be agreed upon and accepted by all involved parties (consensus finding) (Paillisse et al., 2019). The group of involved responsible(s) makes decisions for the whole network – implying whether the information is added to the chain. The same applies to extending the network by adding firms or users to the chain, where the private blockchain owner decides who can access the chain (Paillisse et al., 2019). The benefits of a private blockchain are greater the more participants are in the network, and the more complex the interdependencies between processes or data are. This is because blockchains reduce administrative tasks, verification, and accounting tasks. Accordingly, private blockchains find use for companies operating on cross-organizational supply chains and for all those that operate in association with subcontractors and suppliers.

Building on the example of manufacturing processes, digital twins offers greater transparency for customers and improves customer relations as clients can follow each step of the value creation process; the promised quality can be monitored throughout the whole value creation process (Söderberg, Wärmefjord, Carlson, & Lindkvist, 2017). Similar to the use case in the manufacturing context, the concept of digital twins can positively influence and simplify human resources management (Pivnička, Hrušecká, & Hrbáčková, 2022). The decentralized closed blockchain technology allows indicating and storing of skills of an individual (Pivnička et al., 2022). For that purpose, certificates, references, completed courses indicating a certain skill like teamwork and completed education like university degrees can be stored on a private blockchain. This information is encrypted and only visible to those parties with whom the individual actively shares his skill profile (Viriyasitavat, Anuphaptrirong, & Hoonsopon, 2019). Uploading information or documents also requires access to the private blockchain. Once uploaded and verified, information cannot be changed, which ensures authenticity (Patel, Bothra, & Patel, 2017). At the same time, it is clear who uploaded which documents and when. Thus, credibility can be increased through transparency ensured by the blockchain. If, for example, work certificates are uploaded from accounts of companies and degree certificates from accounts of universities, these have a higher significance than documents uploaded to the blockchain by individuals without a clear educational reference. Since the blockchain prevents the information from being changed subsequently, the authenticity and originality of uploaded documents are ensured (Wang, Zhu, Ni, Gu, & Zhu, 2020). Once information is stored on the blockchain, it cannot be deleted undetected (Golosova & Romanovs, 2018). Likewise, those who are subsequently approved to view and/or add documents to the private blockchain will also be able to see what information was deleted, when, and by whom. Falsification or false information on the blockchain is virtually impossible as the blockchain's cryptographic characteristics ensure safety. With every new piece of data added, a new block of information is made, in which this new piece of data is combined with the information about the previous block using mathematical cryptographic algorithms (Ismailisufi et al., 2020).

Digital skill twins in the context of human resource management offer a safe and transparent copy of an individual's skills, competencies, and accomplishments. It makes false declarations almost impossible but allows human resource managers to get a detailed and clear understanding of an individual's skills and stages of experience.

As our research is about the digital twin in the context of human resource management, we will elaborate on how a digital twin can be realized on the private blockchain to ensure decentralization and forgery protection of the provided information for all parties. This can be achieved by following four steps, which are outlined in Figure 2.

As a **first step**, the individual registers on a distributed ledger platform offering private blockchains such as Hyperledger Fabric, the most popular platform for private blockchains. On this platform, the individual would be the owner and administrator (blockchain authority) of its private blockchain.

As a **second step**, the owner of the private blockchain (in our case, the individual) sends out invitations to organizations or other individuals in order to join the blockchain. Users (companies or individuals) are permitted to view and add data to the blockchain. This results in a peer-to-peer architecture. Before data are added to the chain, a consensus chain of blocks is implemented.

The **third step** is about proposing data to be added to the chain. The related data gets only added to the private blockchain if the consensus mechanism allows it to do so. As indicated, the consensus mechanism in a private blockchain is reached when all members of the chain agree with the data to be added. For instance, if a university wants to add a certificate of a certain skill to the chain, it needs to be confirmed by all members of the chain. The lecturer needs to prove that the certificate is real and that the individual has the skill.

In the **fourth step,** the data is added to the chain. As soon as data are uploaded to the private blockchain, they cannot be deleted anymore (Heshmati et al., 2022). This is especially valuable for HR as it allows recruiters to get a detailed and transparent idea of an individual's skills. At the same time, this digital twin can be used for making propositions of which courses to attend to make a profile more attractive. The bigger the base of organizations or individuals that prove certain skills, the greater the consensus. The cryptographic characteristics of blockchain ensure safe and secure data transfer. By having a robust authentication of users and data sources, data immutability along with the safety of digital twins promises a lot for using the new concept for human resources management and provides solutions to challenges such as the signaling theory perspective.

Insert Figure 2 about here

3 FUTURE RESEARCH

Assessing skills through a digital twin is an important prerequisite for equipping professionals with knowledge about their strengths and possible developments. It also provides individuals and organizations with the reliability and objectivity needed to obtain an overview of skills. The aim of this conceptual paper is to show how digital twin technology can be applied to employee skills to support human resource management. To this end, we theorize the concepts involved and developed five assumptions necessary to realize our framework of the digital skill twin. In the following, we discuss important implications for future research approaches (FA).

We propose empirically testing the digital skill twin's assumptions for future research. In doing so, it makes sense to advance the development of a digital skill twin through research. Since a systematic skill assessment needs a sound conceptual basis, a first paper could address the question of what a skill taxonomy should look like and which skills it should include. A state-of-the-art literature review combined with surveys of different professional groups focused on 21st-century skills (information and technology, communication and collaboration, and critical thinking and problem-solving) would be useful. Another method could be text mining. This method extracts relevant terms, descriptions, and skills characteristics. This can be based on existing online databases such as ESCO (European Commission, 2022) and O*NET (U.S. Department of Labor/Employment and Training Administration, 2022), which provide structured data on skills (Fareri et al., 2021) or by referring to own data (e.g., Smaldone, Ippolito, Lagger, & Pellicano, 2022). Then, the results are transferred into a taxonomy with categories for skills, their characteristics, and operationalizations (Nickerson, Varshney, & Muntermann, 2013) *(FA #1).*

Having accomplished this, one can turn to the question of how these skills can be operationalized and captured in an automated way. Due to the amount of data needed for a digital skill twin, automated or at least semi-automated skill assessment methods are beneficial for saving resources. Some studies already address automated approaches to programming skill assessment (Ala-Mutka, 2005; Ihantola, Ahoniemi, Karavirta, & Sepälä, 2010; Souza, Felizardo, & Barbosa, 2016). However, many of them lack a conceptual foundation (Souza et al., 2016), which in this case would be provided by *FA 1*. Again, a literature review may be helpful, or a meta-study that refers to the empirical effects of existing operationalizations of skills. At the same time, analyzing the existing operationalizations of skills concerning their sources and methods would be possible *(FA #2).*

Our concept of the digital skill twin presented here offers various application scenarios for practice and research, which will be interesting to explore in the future. Among other things, there is great potential in using this technology for online labor markets and freelancers. Many freelancers offer their services via online platforms such as Upwork or Amazon Mechanical Turk, so-called online labor markets. This has several advantages for the freelancers, such as saving time and effort in the placement process, as they can be directly contacted by companies or apply for projects themselves. Also, they can directly compare their skills with potential assignments to select the most suitable ones, which applies the other way around for the clients. Most freelancers are active on more than one platform to make the most of these advantages. But for each of these platforms, a new skill profile is necessary, i.e., the entry of mostly identical data. This is where our digital skill twin can come in handy. With a decentralized skill profile on the blockchain, freelancers could save themselves much effort. At the same time, there would be the possibility for the platform operators and the clients to ensure that no false information about the skills has been provided and that these have been verified several times. It would also be possible to expand the digital skill twin during projects on the OLPs. Consequently, a research question could deal with how a digital skill twin will be integrated into existing OLPs *(FA #3).*

Another application scenario is to use digital skill twin technology for re& upskilling processes within organizations by combining continuous insights about skills, predictions about potential development paths, and suggestions for specific tasks or projects (Wu, Yang, Cheng, Zuo, & Cheng, 2020). This seems particularly relevant, considering that 41% of employees cite a lack of professional development and advancement opportunities within the organization as the top reason for quitting (Statista, 2022). For example, automated skill matching can help workers and companies match skills and advancement opportunities. Finally, the development of a digital skills twin that can automatically capture information and match it to the appropriate categories, as well as predict relevant training programs or required skills for a given task or project, will help significantly improve career development and staffing processes (Furini et al., 2022). Specifically, this can be done through machine learning algorithms that analyze the twin and create training or materials for improvement. Therefore, one research question may be: How can digital skill twins improve professional development and HR processes? Based on the previous research questions, this thesis should investigate the possibilities of digital skill twins. The focus is on the possibilities of a digital skill twin in practice. For example, using a mixed-methods approach consisting of interviews with HR managers and project managers and surveying employees, the applicability of HR work processes, especially in supporting employee development paths, can be inquired *(FA #4).*

The digital skill twin framework also poses challenges for future research, the potential of which we wish to highlight here. Legal and ethical considerations are necessary to bring this idea to life. The question of who owns the data should be easy to answer, that the data belongs to the employee that the twin represents. Nevertheless, the question arises as to who is allowed to make entries or view them. To date, legal theory has focused primarily on the tension between the individual, the state, and the market, attempting to unite competing for power dynamics and strike a balance between public interests, state interests, and private interests (Wright & Filippi, 2015). However, there is no legal guidance yet for blockchain, which is tangential to all of these areas. This makes it vulnerable to abuse and unregulated (Wright & Filippi, 2015). Bringing these considerations in line with data protection can provide a further direction for research *(FA #5).*

We identified the relevance and advantages digital skill twins would have with using blockchain technology. However, legal challenges, transaction cost challenges, and network effects will influence the realization of the digital skill twin. For instance, the question of the concrete depiction of the blockchain and whether this should be a centralized or a decentralized blockchain or a combination of both arises *(FA #6).*

Lastly, although we have omitted it from this conceptual paper, it is interesting for future research to look at the presentation layer in more detail. Above all, it would be interesting to ask how the user interface of a digital skill twin must be structured in order to create added value and meet user acceptance *(FA #7).*

4 CONCLUSION

Accurate measurement of employee capabilities is of paramount importance, especially in the changing world of work. It is, therefore, important to adapt the underlying assumptions and methods to these changes. Digital twin technology offers ideal opportunities for this. Through this technology, skills can be recorded reliably. In summary, a clear picture of an individual’s skills can be achieved by using a valid database consisting of multiple sources for a skill (e.g., resumes, certificates) captured by different methods (e.g., 360-degree feedback, NLP). We argue for a holistic view of 21st-century skills in particular, as a single aspect cannot describe skills such as information and technology, communication and collaboration, and critical thinking and problem-solving. The appropriate operationalization and the underlying methods could differ for each skill. We also argue for a dedicated conceptual exploration of skills and their operationalizations. Data storage is decentralized, and ownership rests with the individual, which also allows for the possibility of scaling. Overall, the results provide deeper insight into how skills assessment can be automated and what opportunities to use this data to create significant value for employees and employers.

Our research provides theoretical and practical contributions. Our work contributes to a type V explanatory theory (Gregor, 2006) by presenting operating principles and integrating theoretical knowledge used to develop a technology. We contribute to theories that deal with the development of skill profiles and the automation potential of human resource processes. By demonstrating a new framework that can capture skills and make data-based decisions, analyses, and even predictions based on them. In addition, we provide an approach to apply the digital twin technology to a new application domain to scale the benefits of this development. This combination helps us derive areas for future research studies for our readers that address the specific aspects of a digital skill twin.

We support practitioners in their understanding of how skill assessment requirements are changing and what potential pathways exist to improve workers' skills and leverage existing potential. In order to obtain and present these insights, we propose a framework that measures and analyzes skills. In doing so, this conceptual paper offers practitioners guidance on how the digital skills twinning approach could enable reliable and objective assessment of employee competencies. This paper bridges the gap to data-driven skills identification. On this basis, it is possible to empower employees to develop their skills independently and equip organizations with the necessary knowledge to make the most of their employee' skills and identify appropriate development paths for them.

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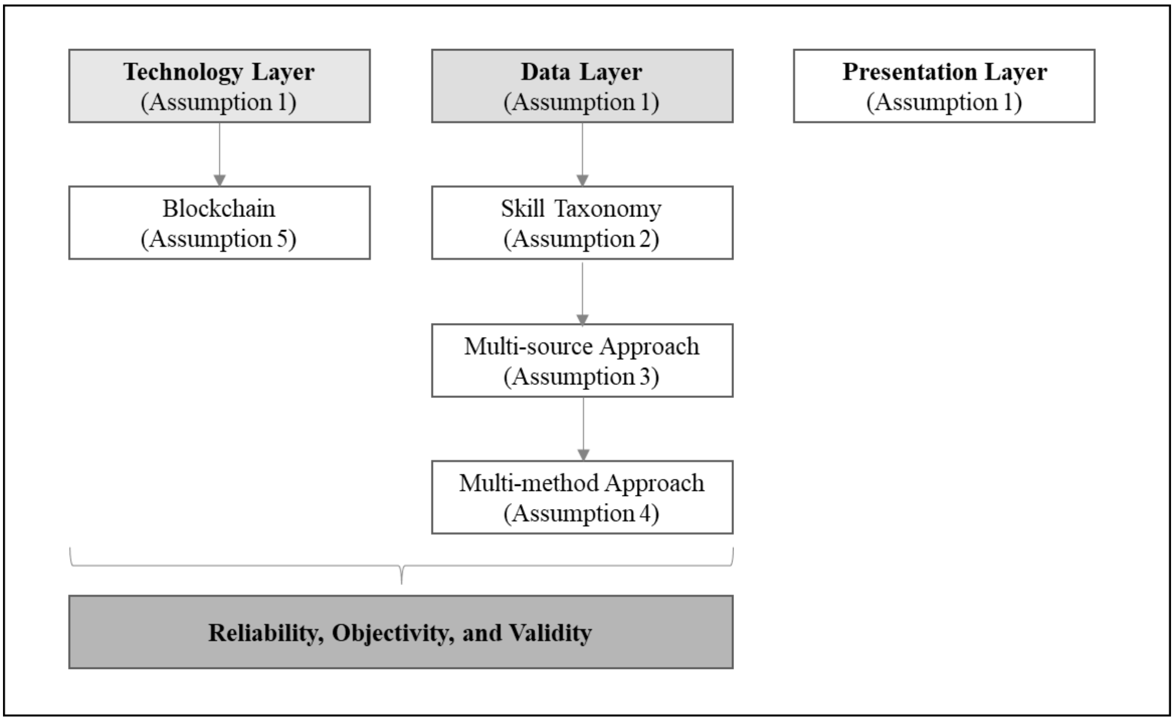

FIGURE 1: Framework of Digital Twin including Assumptions

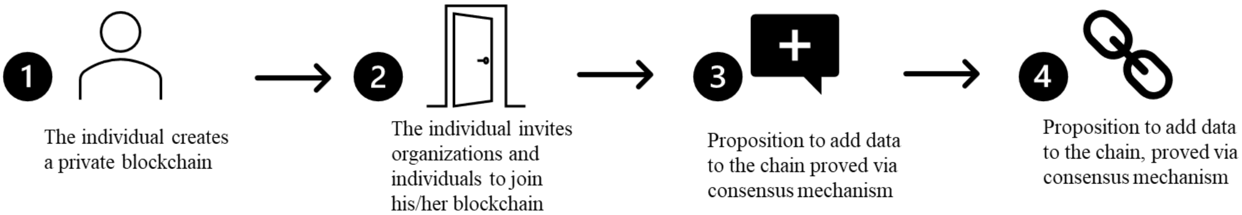

FIGURE 2: The Mechanism of Blockchain as a Solution for a Digital Skill Twin