SMART SKILLS DECISION-MAKING TOOL FOR WORKFORCE 4.0 TECHNOLOGY PROFILE SELECTION

FERRAMENTA INTELIGENTE DE TOMADA DE DECISÃO POR COMPETÊNCIAS PARA SELEÇÃO DE PERFIL TECNOLÓGICO DA FORÇA DE TRABALHO 4.0

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ABSTRACT
The study proposes a smart decision-making tool for skills needed to select the ideal technology profile for the workforce 4.0. Based on the design science methodology, we first performed a systematic literature review using the PRISMA methodology to identify skills underlined by the literature. A relative importance index (RII) was then adopted to rank the skills. Our findings show that soft skills are essentially similar regardless of digital technology. Additionally, hard skills seem more diversified owing to the technology presented. Furthermore, our findings suggest that each technology requires a different level and range of skills. A dashboard was built to present a smart decision-making tool for mapping skills related to Industry 4.0. This research contributes to the needs of the workforce by identifying and recruiting profile definitions, implementing role-changing and change management, and reskilling and upskilling people in companies that embarked on the digital initiatives of Industry 4.0, defining a skill-based technology profile 4.0. The paper presents contributions on a tool to assist leaders and Human Resource Management 4.0 to effectively manage skills in times of digital transformation. Thus, the paper is original in that it presents a decision-making tool to help relate and integrate a worker's skills in Industry 4.0 and its disruptive technologies, establishing a decision of the ideal technological profile 4.0 of the ideal worker for Industry 4.0.
Keywords: Industry 4.0. Human Resource Management 4.0. Skill Mapping. Smart decision-making. Smart Tool. Digital Technologies.

RESUMO
O estudo propõe uma ferramenta inteligente de tomada de decisão por competências necessárias para selecionar o perfil tecnológico ideal para a força de trabalho 4.0. Com base na metodologia design science, foi realizado uma revisão sistemática de literatura utilizando a metodologia PRISMA para identificar as competências na literatura. A partir disso, foi adotado o índice de importância relativa (IIR) para classificar as competências. Como conclusões, as competências socioemocionais são essencialmente semelhantes, independentemente da tecnologia digital utilizada. Por outro lado, as competências técnicas parecem ser mais diversificadas em consoante a tecnologia utilizada. Além disso, nossos resultados sugerem que cada tecnologia requer um nível e uma gama de competências diferentes. Foi criado um dashboard para apresentar a ferramenta de tomada de decisão inteligente de forma a criar um mapa de competências relacionadas a indústria 4.0. Esta investigação contribui para as necessidades da força de trabalho, identificando e recrutando perfis definidos de acordo com as tecnologias, requalificar a força de trabalho e melhorar a identificação das competências 4.0 necessárias para as empresas adentrarem ao mundo da indústria 4.0. O artigo apresenta contribuições sobre uma ferramenta para ajudar os líderes e a Gestão de Recursos Humanos 4.0 a gerir eficazmente as competências em tempos de transformação digital. Assim, o artigo é original na medida em que apresenta uma ferramenta de tomada de decisão para ajudar a relacionar e integrar as competências de um trabalhador na Indústria 4.0 e suas tecnologias disruptivas, estabelecendo uma tomada de decisão do perfil tecnológico 4.0 ideal do trabalhador para a Indústria 4.0.
Palavras-chave: Indústria 4.0. Gestão de Recursos Humanos 4.0. Mapeamento de Competências. Tomada de decisão inteligente. Ferramenta inteligente. Tecnologias Digitais.

1 INTRODUCTION

Industry 4.0 is characterized by the adoption of digital technologies in industrial environments (REISCHAUER, 2018; DOS SANTOS FILHO; DE RESENDE; PONTES, 2024). The use of technology such as artificial intelligence (AI) requires revolutionizing the labor market, because the more intelligent the system, the more data is generated; consequently, qualified workers are needed (CAGLIANO et al., 2019; JERMAN et al., 2020). Digital technologies are necessary for Industry 4.0 to function and work together according to the company's need for digitization (BONGOMIN et al., 2020; KAASINEN et al., 2019; SOLTOVSKI et al., 2020). There is no consensus in the literature regarding the number of digital technologies belonging to Industry 4.0 (BONGOMIN et al., 2020). However, studies (DA COSTA et al., 2019; KERIN; PHAM, 2019) point to the Internet of Things and cyber-physical systems as the main groups of technology. Additionally, trends in the use of AI, especially human resource management (HRM), are evident (ABDELDAYEM; ALDULAIMI, 2020; DA SILVA et al., 2022; NAIR, 2019).

A series of skills are required to use digital technologies in a meaningful way to contribute to the business (MAISIRI; DARWISH; VAN DYK, 2019). Organizations need to help workers upskill and reskill (DA SILVA et al., 2022; DO; YEH; MADSEN, 2016) because the difference between the traditional workforce to the workforce 4.0 is related to the knowledge and skills gap; in addition to its operationalization, the management of decision-making about the data generated is required (GALATI; BIGLIARDI, 2019; NARDO; FORINO; MURINO, 2020). Additionally, there is a trend of collaborative work between humans and machines, promoting the well-being of people and leveraging their soft skills with the ability of intelligent machines to create multidisciplinary teams (LU et al., 2021, 2022).

HRM is not only focused on selecting, hiring, and firing workers but also on learning, training, and developing worker's skills (BENEŠOVÁ; TUPA, 2017). The Fourth Industrial Revolution has brought about more rapid and impactful transformations, and challenges to the workforce (RASCA, 2018; SIVATHANU; PILLAI, 2018). The Fourth Industrial Revolution has brought about more rapid and influential transformations than previous ones, posing a challenge to human resources (RASCA, 2018; SIVATHANU; PILLAI, 2018), especially in terms of employment, workforce, and skill development (NANKERVIS et al., 2019; SILVA et al., 2019). Owing to the importance of people and how issues such as skills, qualifications, and learning frameworks are relevant issues for the future agenda of organizations, enabling people to use digital technologies effectively is crucial (MOLINO; CORTESE; GHISLIERI, 2020).

Therefore, skill mapping is important for smart decision-making support of organizational performance, facilitating higher levels of skills for workers (MITTAL; DHIMAN; LAMBA, 2019). Skill mapping guides workers to acquire new skill sets and pinpoints the most important ones and the ones that need

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improvement, hence influencing worker performance (BUSAIBE et al., 2017; PIO et al., 2021) creating an appropriate technology profile as digital technologies used (BILBAO-UBILLOS; CAMINO-BELDARRAIN; INTXAURBURU, 2021). The technological profile 4.0 is characterized by the profiles linked to digital technologies arising from industry 4.0.

However, there is a gap in the studies related to the mapping and grouping of skills based on digital technologies for Industry 4.0 (DA SILVA et al., 2022). Regardless of the number and type of technologies, Industry 4.0 starts from the principle of analyzing large amounts of data for decision-making and agile responses, providing flexibility and efficiency in the application of digital technologies. This changes the skills required from the workforce (KIPPER et al., 2021; PATTANAPAIROJ; NITISIRI; SETHANAN, 2021). This proposal helps HRM 4.0 understand the skills of its workforce and can assist HRM-management in tasks related to recruitment and selection, learning and training, talent management, rewards, and performance management (DA SILVA et al., 2022; ROSA et al., 2023), and leaders in establishing strategies (DILLENBURG; FROEHLICH; BOHNENBERGER, 2023).

Recent research has pointed out gaps related to the skills needed in Industry 4.0 contexts and the difficulties in defining the levels of skills needed for recruiting, reskilling, and upskilling the workforce (DA SILVA et al., 2022). They also evaluate the potential of skills mapping and the challenges faced by companies in assessing skills needs, especially in a context of rapid change led by the ongoing evolution of digital technologies. This research aims to address some of these gaps: RQ1 "How can the important skills for Industry 4.0 be mapped?"; RQ2 "What are ways to measure the skill levels of workers based on their use of digital platforms for smart decision-marking skills for technology profile 4.0 worker?" By answering these questions, this study contributes to the formation of a decision-making tool related to the mapping of skills for recruitment, selection, and training of workers according to the technology profile in the context of Industry 4.0. Identifying the mapped skills that contribute to achieving Sustainable Development Goals (SDG), especially SDG 8 (Decent Work and Economic Growth) and SDG 9 (Industry, Innovation, and Infrastructure).

The study proposes a smart decision-making tool for skills needed to select the ideal technology profile for the workforce 4.0. Accordingly, the study conducted a systematic literature review (SLR) to identify a series of soft and hard skills to be evaluated based on the analysis of the relative importance index (RII). The RII method was used to analyze the importance of skills based on the data collected from researchers and industry professionals. In conclusion, a dashboard was proposed to aid in the smart decision-making process to further determine the skills important for one or a set of technologies. The dashboard was built using Microsoft Power BI software (MICROSOFT, 2022). It will be useful for recruiters, human resources managers, and industry leaders to understand the skills required for a particular job position.

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2 MATERIAL AND METHODS

The construction of the dashboard for smart decision-making was based on the design science methodology (DRESCH, 2020; HEVNER et al., 2004). Its primary aim was to seek an understanding of the problem and construct and evaluate transformations in the described problem situation. Design science is suitable for research activities that feature the application of knowledge (COLLI et al., 2021; VAN AKEN; CHANDRASEKARAN; HALMAN, 2016). The steps used in this study are listed in Table 1.

Table 1 - Research Steps

Design Science Phases	Steps	Description	Results
Phase 1. Literature Review	1. Problem Definition	Gap identification and formulation of the research question	RQ1 "How to map important skills for Industry 4.0?"; RQ2 "What are ways to measure the skill levels of workers based on their use of digital platforms for smart decision-marking skills for technology profile 4.0?"
	2. Development of the Literature review	Systematic Literature Review of the PRISMA methodology to identify studies that present the skills relevant to Industry 4.0.	Final portfolio with 56 studies and seven research reports that present soft skills and hard skills important for Industry 4.0.
Phase 2. Development of the conceptual framework	3. Development of the Survey	Development survey instrument to be sent to industry and university experts.	The survey questionnaire examined the relationship between 26 identified soft skills 28 identified hard skills, and the 13 identified digital technologies to be presented to the experts.
Phase 3. Application of the conceptual framework	4. Data Collection	Collect data from the experts regarding the skills level of digital technologies	Collecting 18 experts from industry and academia about their experience with certain digital technologies in Industry 4.0.
Phase 4. Evolution of the conceptual framework	5. Data Analysis and Results	Generate the numerical indicators based on RII and present the 10 most important soft skills and 10 hard skills for each digital technology	Formulation of a skills map with the top 10 soft skills and top 10 hard skills for each digital technology.
Phase 5. Improve the conceptual framework	6. Artefact Development	Construct a dashboard for smart decision-making based on digital technologies and their requisite skills.	Dashboard developed with the collected data, thus functioning as a smart decision-making tool, allowing for the verification of the importance of soft and hard skills for each digital technology.

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2.1 SYSTEMATIC REVIEW OF LITERATURE (PHASE 1)

The construction of skill mapping was aided by a theoretical base formulated through a systematic literature review and content analysis. The systematic review aimed to analyze relevant evidence, conducting a systematic and replicable process to highlight pertinent literature (KITCHENHAM, 2004).

For this study, the Preferred Reporting Items For Systematic Reviews And Meta-Analyses (PRISMA) methodology was used. This methodology allows for an investigation of the theme and an analysis of the studies published in the selected databases (PAGE et al., 2021), investigating studies from a particular perspective. Table 2 shows the research protocols used.

Table 2 - Research Protocol

Search Keywords (Title-Abs-Key)	**Group 1 – Industry 4.0** ("Industry 4.0" OR "Industrie 4.0" OR "Fourth Industrial Revolution" OR "4th Industrial Revolution" OR "Smart Industry" OR "Smart Manufacturing" OR "Smart Factory" OR "Digital Transformation") **Group 2 – Skills** ("Skill" OR "Competence" OR "Competency" OR "Human Resource Management" OR "HRM")
Search Strategy	AND among groups
Database	Scopus (707 documents), ScienceDirect (107 documents), Web of Science (309 documents), and other sources (6 documents)
Publication Type	Research Paper and Review Paper
Language	English
Search Period	2013–2022

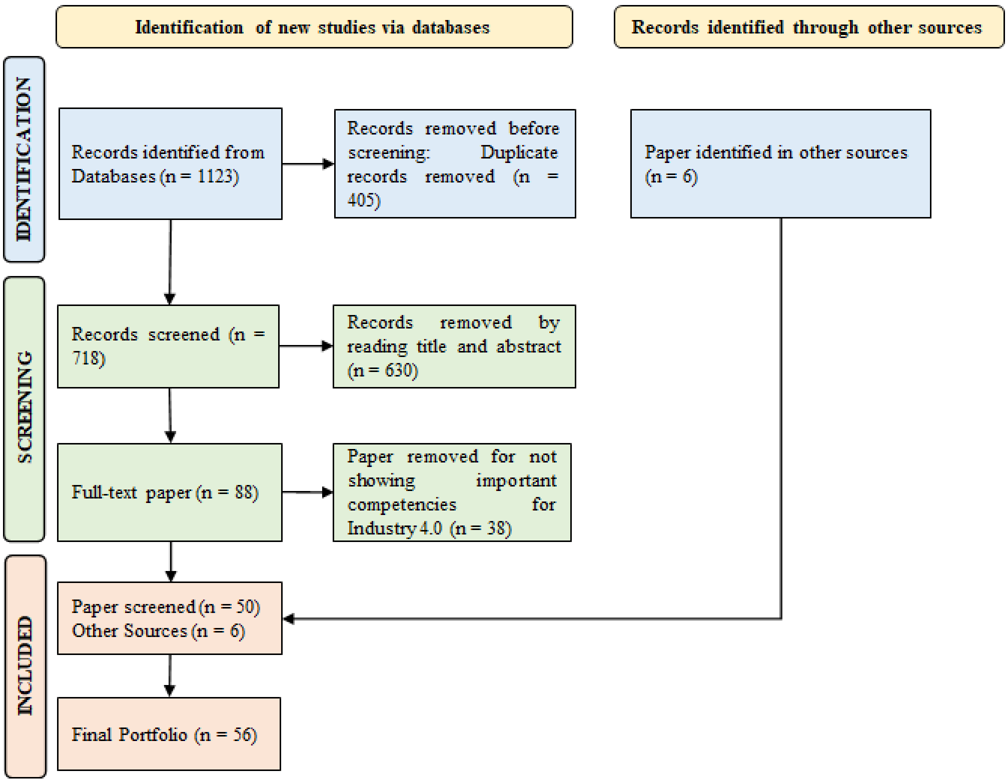
Source: Author's elaboration.

The search keywords represent words defined by the research groups, Industry 4.0 and skills. There are some synonyms for Industry 4.0, as there are some actions worldwide that represent this advance in the Fourth Industrial Revolution. Industry 4.0, Industrie 4.0, and the Fourth Industrial Revolution are terms used in Germany, while advanced manufacturing and smart factories are terms used in the United States (SAKURADA et al., 2021; RODRIGUES et al., 2021). To identify studies about the skills group, we searched for the term's skills, competence, competency, skill, and human resource management.

The PRISMA methodology is divided into three stages. The identification step allowed us to collect files from the databases according to the established search protocols. As three different databases were used, it was necessary to eliminate duplicate articles. This step also included the identification of articles from other sources, such as references of articles that were not returned to the database.

The screening stage allowed us to narrow the bibliographic portfolio further to meet the proposed objectives. First, articles were excluded based on their titles and abstracts. Later, when the complete text of the article was read, the objective was to identify important skills for Industry 4.0. Therefore, the articles excluded in this step did not discuss these skills. Therefore, the final portfolio of articles comprised studies that presented important skills for Industry 4.0. Figure 1 shows the steps taken, and the number of studies included or excluded in each step.

Figure 1 - Steps of PRISMA



Source: Author's elaboration.

To complement the list of competencies, this study used reports that discussed skills in the labor market in the context of Industry 4.0. This allowed for a more comprehensive investigation of the discussion of competencies. We used reports from the World Economic Forum, McKinsey, Delloite, SESI, and government initiatives such as vocational education and training (VET). After including the reports, a total of 63 documents were analyzed for content analysis.

Content analysis is guided by the intent to build knowledge, generate theories, and develop models by organizing qualitative data. It synthesizes findings to analyze the existing gaps in scientific knowledge (BRAUN; CLARKE, 2006; BRINGER; JOHNSTON; BRACKENRIDGE, 2004). From the content analysis, the important skills for Industry 4.0 were identified; twenty-six soft skills and 28 hard skills thus identified are presented in Table 3.

Table 3 - Skills for Industry 4.0

Category	Skills	Main Authors
Soft Skills	Problem-Solving; Communication Skill; Teamwork; Creativity; Lifelong Learning; Leadership; Flexibility; Critical Thinking; Decision Making; Emotional Intelligence; Analytical Skill; Adaptability; Compromising and Cooperation; Ethic or Integrity; Intercultural Skill; Autonomy; Entrepreneurial Thinking; Networking Skill; Transfer Knowledge; Work Under Pressure; Conflict Solving; Negotiation; Empathy; Sustainable Mindset; Self-Confidence; Digital Mindset.	(ANSARI; HOLD; KHOBREH, 2020; AZMI et al., 2019; CAPUTO et al., 2019; GOLOWKO, 2018; KAMARUZAMAN et al., 2019; LIBONI et al., 2019; WORLD ECONOMIC FORUM, 2020)
Hard Skills	Programming; Understanding IT Security; Digital Literacy; Data Analysis; Information and Communication Technology; Process Understanding; Media Skill; Language Skill; Research Skill; Simulation; Project Management; Internet of Things; Cloud Computing; Artificial Intelligence; Big Data; Maintenance and Repair; Knowledge of Software 3D; Service Orientation; Augmented Reality System; Application Development; Computer Architecture; Statistic; Software Development; Autonomous Robots; Machine Learning; Embedded Systems; Database Administration; Mathematical Thinking.	(JAGANNATHAN; RA; MACLEAN, 2019; JERMAN; PEJIĆ BACH; ALEKSIĆ, 2020; LISZKA; KLIMKIEWICZ; MALINOWSKI, 2019; MAISIRI; DARWISH; VAN DYK, 2019; MCKINSEY GLOBAL INSTITUTE, 2018; RAMPASSO et al., 2020; SAKURADA et al., 2021; SESI, 2020)

Source: Author's elaboration.

Additionally, 13 digital technologies that are part of Industry 4.0 were identified, based on the studies of (AGRAWAL et al., 2020; RUBMANN, 2015; VAIDYA; AMBAD; BHOSLE, 2018), namely: Internet of Things, Cyber-Physical Systems, Big Data, Virtual and Augmented Reality, Simulation, Additive Manufacturing, Cyber Security, Cloud, Autonomous Robots, System Integration, Artificial Intelligence, Machine Learning, and Smart Sensors. Therefore, depending on your needs, skilled labor is required to implement and use digital technologies.

2.2 SKILL MAPPING TOOL (PHASE 2)

The survey aimed to collect the specialists' points of view, attributing the importance of the skills described about digital technology. For this, the experts used a 5-point Likert scale (1 = not important, 2 = slightly important, 3 = of medium importance, 4 = important, 5 = very important). The mathematical model chosen for the surveys was based on the relative importance index (RII). This index was used owing to its flexibility. Its flexibility is related to the number of respondents and can transform the answers

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into an index regardless of the number of respondents. RII ranks attributes according to their relative importance (ROOSHDI et al., 2018), as shown in Equation 1:

$$RII = \frac{\sum W}{A \; x \; N} \quad (1),$$

Where:

- W = the weighting assigned by each respondent on a scale of one to five;
- A = the highest weight;
- N = the total number of samples.

Based on Equation 1, the answers were converted into an index from zero to one, where the closer the score is to zero, the less important the skill is for the digital technology evaluated. The closer the value is to one, the more important the skill is for the evaluation of digital technology. Although the survey returned different amounts for each technology, the calculation represented the experts' opinions without losses or differences in the indices found. Therefore, the purpose of mapping and ranking skills was achieved.

2.3 DATA COLLECTION (PHASE 3 AND 4)

The experts used criteria based on their knowledge of Industry 4.0. University experts were chosen based on their research in Industry 4.0; these experts are part of disciplines and projects that involve driving technologies. Regarding industry, the choice was based on Industry 4.0 project leaders in partnership with the Federal University of Technology - Parana, and addressed via the social business network LinkedIn.

The survey was sent to 43 people, including professors from South America, North America, and Europe, and industry professionals. Of the 43 surveys sent, 18 were returned. To be considered valid, from the moment an expert discusses a technology, they should have an opinion about all the skills described. Table 4 shows the characteristics of respondents concerning continent, organization, and position

Table 4 - Characteristics of Respondents

Continent	Organization		Position		
	University	Industry	Professor	Management	Operation
South America	8	5	44,4%	16,66%	11,11%
North America	1	0	5,55%	0%	0%
Europe	3	1	16,66%	5,55%	0%

Source: Author's elaboration.

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2.3 DASHBOARD FOR SMART DECISION-MAKING (PHASE 5)

From the data collected, a tool to support intelligent decision-making was constructed. Business intelligence tools, such as the one used by this study, Power BI (MICROSOFT, 2022), represent the starting point for facilitating the visualization of a set of intelligent data, allowing the user to extract information with greater ease (GRÖGER, 2018).

Therefore, a suitable tool has been adapted to make decisions based on a worker's skills or to determine which skills are required by technology. Additionally, it functions as a database for organizations as a collection of skills, and even for research studying new parameters related to skills and digital technologies.

3 RESULTS AND DISCUSSION

To obtain the skills map according to the digital technologies relevant to Industry 4.0, the experts were asked for their opinions regarding the level of importance in the relationship between skill and technology. For a better understanding, the skills were subdivided into soft and hard skills. Appendix I presents the relationship between soft skills and digital technologies, presenting only the 10 most important skills for each technology.

The mapping of skills is a specific process based on trend of the digital technologies presented. From the results presented in Appendix I, 12 of the 26 soft skills were chosen as important. As mentioned, only the top 10 were listed in the ranking. However, soft skills were common, regardless of the technology applied in the workplace.

The highest scores were for Ethics or Integrity for the Internet of Things and Analytical Skills for Big Data (0.916). Among the lowest were Teamwork for the Internet of Things and Autonomous Robots, and Critical Thinking for Autonomous Robots, with an index of 0.733. Furthermore, Appendix I clearly shows that machine learning has a balanced IRR of the skills evaluated between 0.800 and 0.900.

Regarding these skills, five soft skills were common in the ranking of the 13 digital technologies: ethics or integrity, problem-solving, digital mindset, communication skills, and critical thinking. These skills are also presented in the studies of (BONGOMIN et al., 2020; KAASINEN et al., 2019; KAMARUZAMAN et al., 2019) as being used to digitize the production process, in training and qualification environments shared with workers, and in virtual factories. These common skills can be used in the recruitment, upskilling, and reskilling of the workforce.

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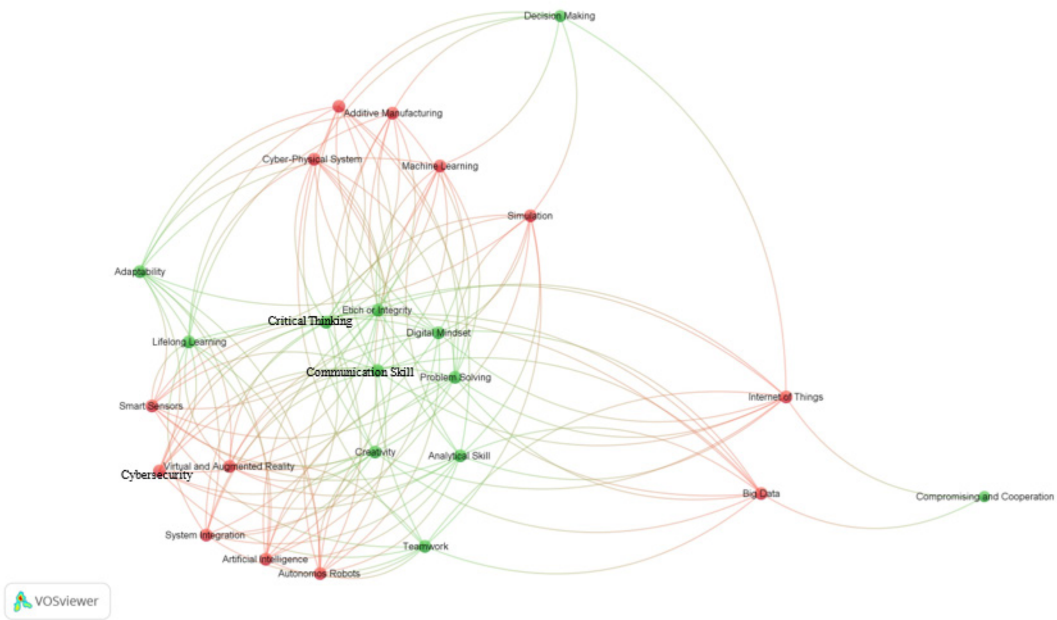
The list of skills is complemented by seven more: compromise and cooperation, teamwork, creativity, analytical skills, lifelong learning, adaptability, and decision-making. Regarding soft skills, the technologies employed do not significantly alter the set of important skills, concluding that relational aspects are common and will serve a wide range of tasks. To present the relationship between the top 10 soft skills and their 13 digital technologies in Industry 4.0, Figure 2 was constructed with the help of Voswier.

Figure 2 - Soft Skills Mapping for Industry 4.0



Source: Author’s elaboration.

The green cluster represents the soft skills found in RII and is considered the most important for the digital technologies evaluated. The red cluster represents digital technologies. The links were presented based on the relationship between soft skills and digital technologies. At the center, the soft skills that have a higher number of connections with digital technologies are presented as ethics or integrity, problem-solving, digital mindset, communication skills, and critical thinking. Further away are the skills that have the fewest links such as compromise and cooperation and decision making.

Such a map process can assist HRM in identifying the skills required according to the technology applied to the work environment. It can assist in the identification of fundamental skills, as proposed by (RUSSO, 2016), which are common to several jobs. Moreover, the set of skills common to different technologies can be developed through training and qualification in conjunction with different jobs that make their application. An example is presented by the technologies of autonomous robots, systems

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integration, and artificial intelligence, which have the same set of soft skills, but with differing levels of importance.

These attributes are related to behavior, personality, and career (FLORES; XU; LU, 2020) and are essential to teamwork and daily communication in the performance of work tasks (CAPUTO et al., 2019; FARERI et al., 2020). It can be concluded that it is necessary to understand, improve, and incorporate these attributes into the training and qualification of workers based on the relevance of these skills and the challenges facing Industry 4.0 (MOLINO; CORTESE; GHISLIERI, 2020; MOTYL et al., 2017; RA et al., 2019).

Appendix II examines the relationship between hard skills and digital technologies and presents the 10 skills for each digital technology. Mapping was conducted based on the digital technology. From the results of the 28 hard skills mapped in the literature, 24 are presented in Appendix II. As mentioned, the top 10 were listed in the ranking. In contrast, regarding hard skills, the skills were more diverse as compared to the soft skills. Regarding the level of importance assessed, hard skills obtained higher scores. When analyzing IoT skills with IoT technology, the relationship score reached 0.950. The same occurred in the relationship between big data skills and big data technology (0.950). The relationship score between simulation skill and simulation technology was 0.983.

This situation occurs when technology also appears as a skill. In the studies investigated, mainly in (ABDELDAYEM; ALDULAIMI, 2020; ÁLVAREZ-FLORES; NÚÑEZ-GÓMEZ; RODRÍGUEZ CRESPO, 2017; JERMAN et al., 2020), skills related to digital technologies such as machine learning or simulation are presented (LEITÃO et al., 2020; PONTES et al., 2021). Industry 4.0 professionals need to have skills related to the technologies. For example, simulation builds real-time data to mirror the physical world, requiring workers to configure and operate the technology (SACKEY; BESTER, 2016).

Depending on which technologies were applied, hard skills presented greater variations. Among the skills presented, two are common among the 13: programming and digital literacy. Additionally, data analytics appeared in 11 out of the 13 technologies consulted. Furthermore, these skills can be considered fundamental, as pointed out by (RUSSO, 2016). Regarding the specific hard skills, one can see, for example, that knowledge of 3D software has a relationship only with additive manufacturing and the autonomous robot skill only with autonomous robot technology, as addressed by the studies of (LISZKA; KLIMKIEWICZ; MALINOWSKI, 2019; MAISIRI; DARWISH; VAN DYK, 2019). Therefore, depending on digital technology, specific hard skills are required for implementation and use.

Additionally, the list offers insights into the skills common across technologies. Cloud and cyber security are digital technologies that have the same set of hard skills. Moreover, common training using these technologies can be offered to workers. To present the relationship between the top 10 hard skills and their 13 digital technologies in Industry 4.0, Figure 3 was constructed with the help of Voswier.

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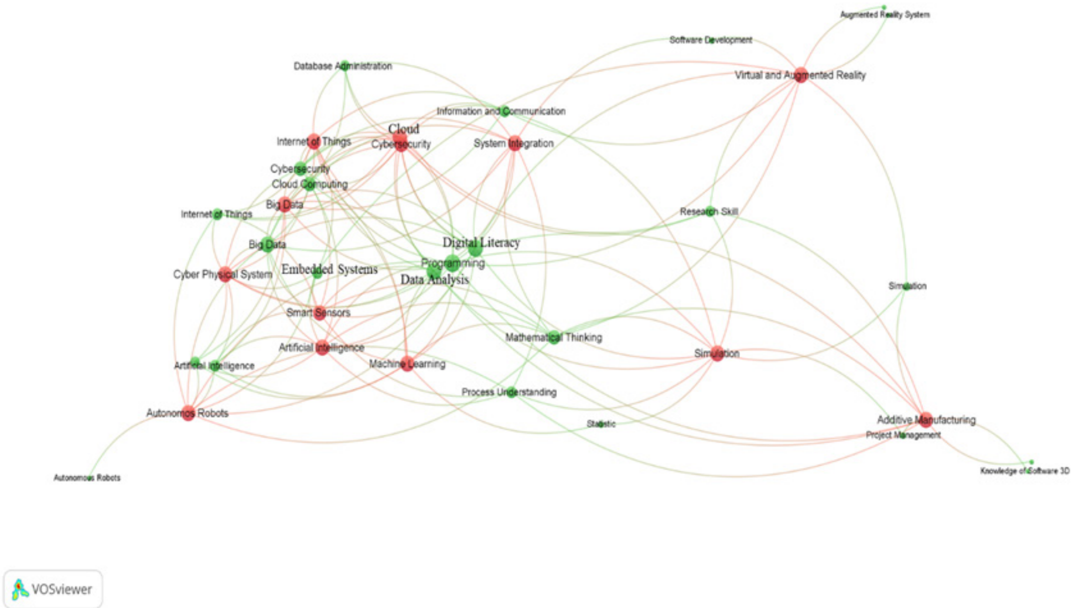
Figure 3 - Hard Skills mapping for Industry 4.0



Source: Author's elaboration.

The green cluster represents the hard skills found in RII and is considered the most important for the digital technologies evaluated. The red cluster represents digital technologies. These links are presented by the presence of a relationship between hard skills and digital technologies. At the center, the hard skills that have a higher number of connections with digital technologies are programming, digital literacy, and data analysis. Further away are the skills that have the fewest links, such as augmented reality systems and knowledge of 3D software.

Unlike soft skills, hard skills can be easily evaluated and learned, enabling improvement over time (MOTYL et al., 2017). The absence of hard skills is also an obstacle to the adoption of Industry 4.0 technologies (CIMINI et al., 2021; MOLINO; CORTESE; GHISLIERI, 2020). This is even more critical than the need for investments, IT security, company size, and changes in organizational culture (DA SILVA et al., 2022). These skills, both soft and hard, need to be followed up by human resource management and play an important role in identifying and developing the skills required in Industry 4.0 (MEDDOUR; ABDUSSALAAM; ABDUL MAJID, 2020).

3.1 SMART DECISION-MAKING SKILLS FOR TECHNOLOGY PROFILE 4.0

The smart decision-making model allows for the presentation of quantitative graphs of the skill levels relevant to each technology. Along with filters that can select the worker's level of mastery over the

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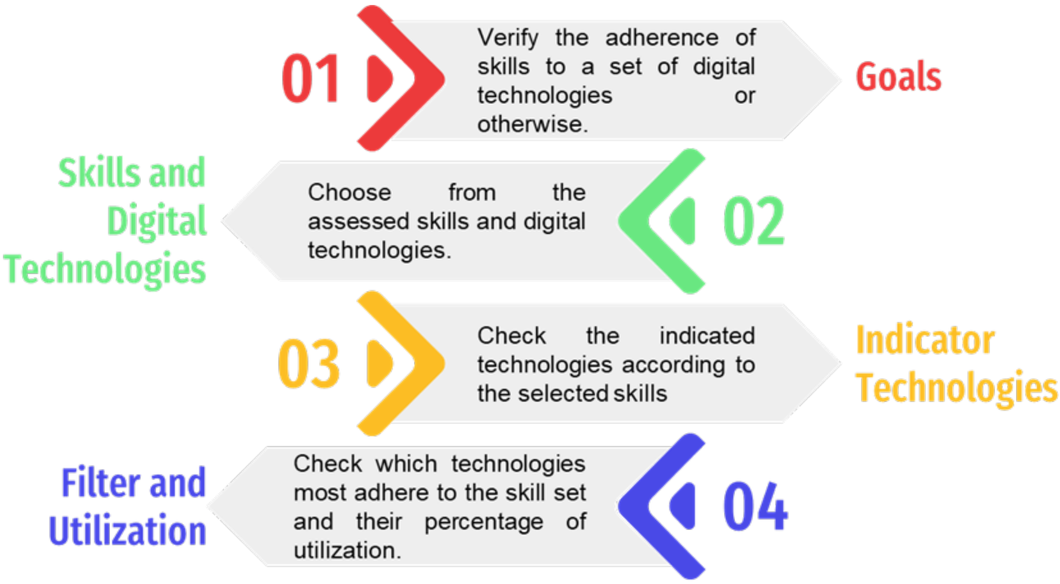
skill or even the skills that are more important for a given digital technology, the decision maker will be aided by real data and can better allocate the worker. The dashboard was built based on the data collected from experts, to present an application using real data, providing quick information regarding the skills required in Industry 4.0. It is useful for recruiters, human resources managers, and industry leaders to understand the skills required for a particular job position. Figure 4 describes the steps involved in using the dashboard.

Figure 4 - Steps to using the dashboard



Source: Author's elaboration.

The first step was to achieve this goal. The dashboard allows one to visualize the need for skills in the digital technologies of Industry 4.0. Therefore, in the process of recruitment staff reallocation, or even changes in a job, the manager can check the adherence of people to that job by knowing the skills required and the digital technologies applied.

The second step refers to the choice of skills and digital technologies to be analyzed. In the selector panel, one can select the set of skills that are subdivided into soft and hard skills. Additionally, in the set of Industry 4.0 technologies, one or several technologies can be selected. The idea of the selection is to graphically visualize the results in Steps 3 and 4.

The third stage involves visualizing the ranking of digital technologies, indicating which one adheres most to the selected skill set. The fourth stage presents the filtering process related to the digital technology and presents their representation in the indicated set in the selected digital technologies. The

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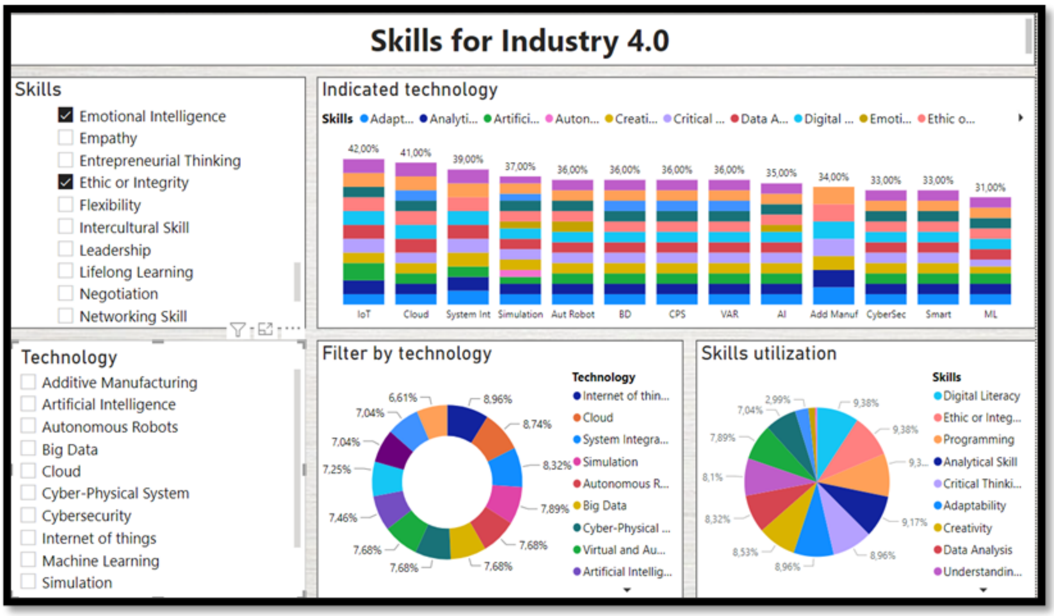
representation of skill utilization presents the most used in an indicated set of 100% among the selected skill sets. Figure 10 shows the dashboard.

The dashboard presented in Figure 5 does not filter technologies, showing a skill domain proportion for all technologies cataloged. In the example shown, among the selected skill sets, the most adherent technology is Internet of Things, Cloud, and Systems Integration, indicating that an evaluated person is more adherent to these technologies according to their skill set.

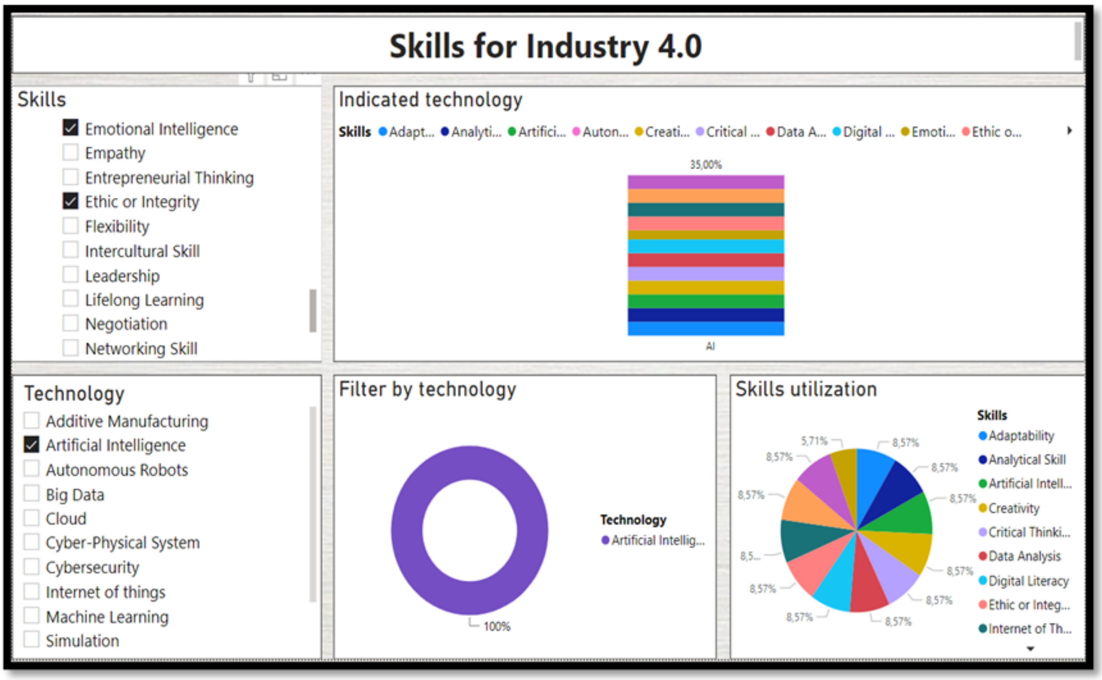
Figure 5 - Dashboard for smart decision-making skills for technology profile 4.0



Source: Author's elaboration.

Once a digital technology is selected against a set of soft and hard skills, the dashboard behavior shows the usage requirements and the need for those skills for the indicated technology. Figure 6 shows an example of artificial intelligence technology.

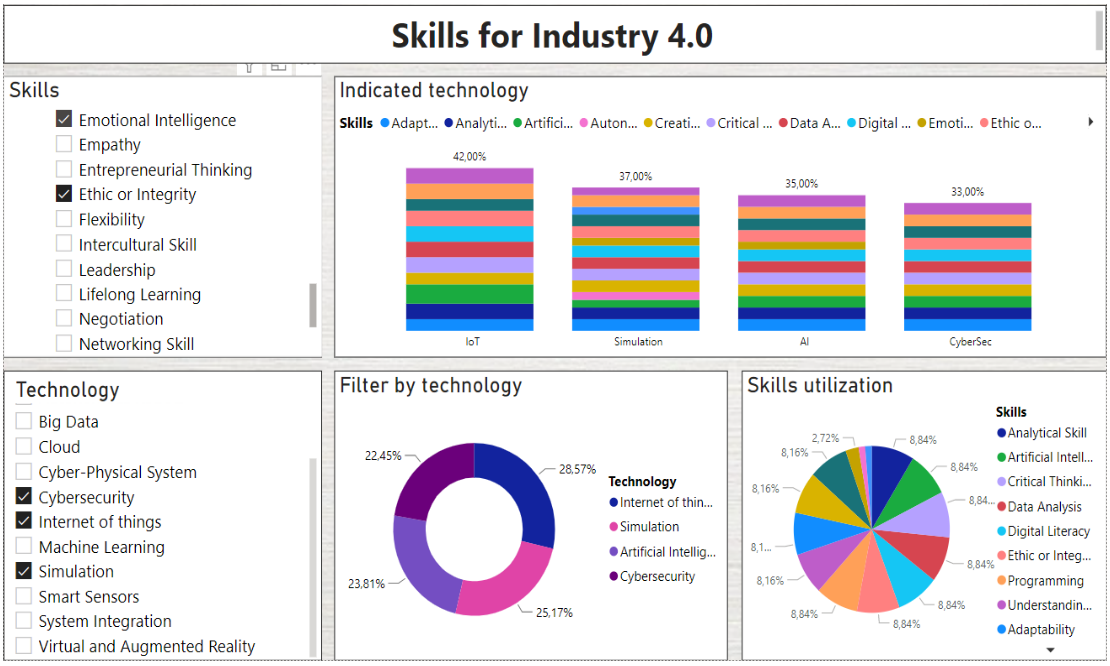
Figure 6 - Skill distribution for technology Artificial Intelligence



Source: Author's elaboration.

Additionally, the intelligent decision-making model adapts to a set of digital technologies that can be part of the workplace. Industry 4.0, which presents the adoption and integration of the manufacturing environment through networking, allows the action of a set of digital technologies that act in a complementary way. Figure 7 shows an example of the distribution of skills indicated for the IoT, simulation, Artificial Intelligence, and cybersecurity.

Figure 7 - Skill distribution for set of digital technologies.



Source: Author's elaboration.

The manager determines the technology best suited based on the level of the worker's competence for each skill. This allows the leader, manager, or human resource management personnel to allocate workers certain roles in the presence of some specific digital technology or even an integration of these. Additionally, when a job profile requires certain digital technology, managers can use technology filtering to understand the composition of skills for a given position. This can assist in HRM decision-making, such as recruitment and selection, and even the development of assertive training according to the needs of workers. The Figure 7 shows filtering by technology.

By filtering by technology, the manager, leader, or HRM can ascertain the skills and levels a worker must possess to work with a particular digital technology. This can help in intelligent decision-making for recruiting new workers, reallocating staff, and providing training for workers according to actual skill needs.

4 CONCLUSION

Throughout the Industrial Revolutions, labor needs, and required skills evolved according to the challenges posed. The Fourth Industrial Revolution, owing to the interconnectedness of the manufacturing environment and digitalization, offers opportunities to shape new job profiles with new skills to help implement and use them more effectively. Scientific studies highlight the critical importance of adapting skillsets to match the rapid technological advancements and complex demands of modern industry. For this purpose, skill mapping is necessary to keep the workforce up-to-date and focus on the interests of stakeholders.

This proposal helps human resource management 4.0 understand the skills of its workforce, recruit more assertively, and provide upskilling and reskilling according to the real need of the skill gap. Recent research in human resource management emphasizes the necessity of continuous skill development and strategic workforce planning to maintain competitive advantage in an evolving industrial landscape. This mapping allows for the construction of a smart decision-making model. This model can assist HRM-management in tasks related to recruitment and selection, learning and training, talent management, rewards, and performance management.

This study directs training programs to reskill and upskill more assertively, seeking new methodologies and educational test-beds based on the demands and challenges imposed by Industry 4.0 and the next evolutionary stage, Industry 5.0. Literature in educational technology and industrial training underscores the value of adaptive learning environments and customized educational pathways to address the specific skill gaps identified. Further, education should be molded based on the real needs of the labor market.

Based on the respondents' answers, it was possible to define a series of soft and hard skills that were important for each digital technology mentioned. The process was conducted by experts in the field, who conducted research or used technology in their work environment. From this, 10 important soft skills and 10 important hard skills for each technology were determined, as shown in Appendix I and II.

These findings corroborate with existing studies that highlight the critical role of both soft and hard skills in navigating the complexities of digital technologies. Based on these results, it is possible to verify the common aspects about soft skills, and the diversity of skills about hard skills. This contributes to the understanding of the changes that have occurred in work skills since the Fourth Industrial Revolution, and the provision of training to the workforce and future workforce to meet new challenges.

4.1 RECOMMENDATIONS, CONTRIBUTIONS OF RESEARCH, LIMITATIONS AND FUTURE SCOPE

Based on the findings, the following recommendations are provided:

- Skill mapping is recommended for HRM to understand the need for skills in the workforce. Skills development is a crucial factor for the success of Industry 4.0 and digital transformation, as pointed out in studies such as Da Silva et al. (2022), Fareri et al. (2020), and Ra et al. (2019).

Workforce training calls for new training programs and tools, using digital technologies such as artificial intelligence, to identify skills gaps and reskilling needs.

- Its use can assist in recruiting, role change, reskilling, and upskilling. Essential HRM tasks to keep the workforce up to date and focused on the implementation and use of Industry 4.0 technologies.
- The process of skill mapping should be used by people, managers, and leaders who have full knowledge of the technology to be mapped so that their opinions about its implementation and use are more assertive.
- The digital dashboard demonstrates the importance of the digital platform to work and make decisions from a large dataset, essential for Industry 4.0.

This study improves the understanding of the skill management system and its use. Therefore, skill mapping helps human resource management to keep the workforce up-to-date and identify skill gaps. Following this identification, it is possible to provide adequate training, recruit effectively, and understand the organization's needs regarding important skills that help the company implement and use the digital technologies of Industry 4.0.

As an academic contribution, the article provides a broad list of important skills for Industry 4.0, mapped from a systematic literature review and analysis of gray literature. In addition, the article advances the literature in terms of offering a smart decision-making tool, making it possible to link skills with one or a set of digital technologies linked to Industry 4.0. From this, with the technology profile drawn up in terms of which digital technologies the worker will be using, it is possible to define a set of important skills that they need to have to work with these technologies. This provides insights for future applications in specific contexts linked to manufacturing, services, or even different generations of the workforce.

This study was conducted to map important skills according to the digital technologies of Industry 4.0. As a proposal for future studies, mapping can be adapted to a set of digital technologies that are employed within a specific company. This enables the delineation of key skills in a specific context. Furthermore, research delimiting job profiles and separation by industry sector is encouraged.

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Appendix 1 - Soft Skills for Digital Technologies

Skills	Internet of Things	Cyber-Physical System	Big Data	Virtual and Augmented Reality	Simulation	Additive Manufacturing	Cyber Security	Cloud	Autonomous Robots	System Integration	Artificial Intelligence	Machine Learning	Smart Sensors
Ethics or Integrity	0.916	0.854	0.900	0.836	0.866	0.780	0.888	0.880	0.866	0.860	0.880	0.880	0.866
Digital Mindset	0.833	0.836	0.866	0.909	0.850	0.860	0.844	0.880	0.844	0.820	0.820	0.840	0.850
Problem Solving	0.816	0.800	0.850	0.863	0.950	0.880	0.911	0.840	0.822	0.840	0.820	0.840	0.850
Communication Skill	0.800	0.836	0.833		0.833	0.780	0.866	0.820	0.777	0.900	0.780	0.800	0.816
Decision Making	0.783	0.763		0.836	0.833	0.780		0.820				0.800	
Creativity	0.766	0.800	0.783	0.818	0.833	0.840	0.822	0.820	0.800	0.800	0.800		0.833
Critical Thinking	0.766	0.818	0.833	0.800	0.850	0.800	0.822	0.780	0.733	0.820	0.780	0.800	0.816
Analytical Skill	0.766		0.916	0.781	0.850	0.800	0.800	0.820	0.777	0.820	0.820	0.840	0.816
Compromise and Cooperation	0.750		0.800										
Teamwork	0.733	0.818	0.850	0.800	0.833		0.822		0.733	0.880	0.800	0.800	0.783
Adaptability		0.818		0.800	0.866	0.780	0.800	0.800	0.777	0.820	0.840	0.840	0.816
Lifelong Learning		0.781	0.800	0.818		0.800	0.866	0.780	0.800	0.840	0.820	0.860	0.866

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Appendix II - Hard Skills for Digital Technologies

Skills	Internet of Things	Cyber-Physical System	Big Data	Virtual and Augmented Reality	Simulation	Additive Manufacturing	Cyber Security	Cloud	Autonomous Robots	System Integration	Artificial Intelligence	Machine Learning	Smart Sensors
Internet of Things	0.950	0.909					0.888	0.800	0.822				0.866
Embedded Systems	0.900	0.890		0.763					0.911		0.860		0.983
Cloud Computing	0.883	0.854	0.933				0.866	0.980		0.760	0.860	0.920	
Programming	0.866	0.854	0.883	0.836	0.900	0.800	0.888	0.880	0.955	0.860	0.880	0.900	0.850
Digital Literacy	0.850	0.854	0.866	0.818	0.850	0.800	0.844	0.880	0.800	0.820	0.860	0.880	0.816
Big Data	0.850	0.854	0.950				0.822	0.880	0.800	0.760	0.860	0.920	0.800
Cyber Security	0.833	0.818	0.850				0.977	0.880		0.840		0.880	0.816
Information and Communication Technology	0.833		0.850	0.763	0.800		0.800	0.840					
Data Analysis	0.816	0.854	0.933		0.850	0.700	0.866	0.900		0.840	0.920	0.940	0.783
Database Administration	0.816		0.933				0.822	0.880		0.840			
Machine Learning		0.872	0.900						0.800		0.880	0.940	
Artificial Intelligence		0.854	0.866						0.866		0.940	0.920	0.783
Augmented Reality System				0.854									
Media Skill				0.800									
Research Skill				0.745	0.783	0.740	0.844	0.780					
Simulation				0.745	0.983	0.780							
Software Development				0.745	0.816					0.840			
Mathematical Thinking				0.745		0.740			0.800	0.780	0.900	0.920	0.800
Process Understanding					0.900	0.800			0.888	0.820	0.860		0.800
Statistic					0.850							0.900	
Project Management					0.783	0.740							
Knowledge of 3D Software						0.760							
Language Skill						0.720							
Autonomous Robots									0.933				