



The worker profiler: Assessing the digital skill gaps for enhancing energy efficiency in manufacturing

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ABSTRACT

In recent years, the manufacturing sector has been responsible for nearly 55 % of total energy consumption, inducing a major impact on the global ecosystem. Although technological advances are increasing its sustainability, zero-emission and fuel-efficient manufacturing is still considered a utopian target. Moreover, a primary feature of Industry 4.0 is the digitization of production processes, which offers the opportunity to optimize energy consumption. However, given the speed and often unpredictability with which innovation manifests itself, tools capable of measuring the impact that technology is having on professions are still being designed. In light of the above, in this article we present the Worker Profiler, a software designed to map the skills currently possessed by workers, identifying misalignment with those they should ideally possess to meet the renewed demands that digital innovation and environmental preservation impose. In more detail, the authors inferred the key technologies and skills for the topic, isolating those with markedly increasing patent trends and identifying green and digital enabling skills and occupations. Thus, the software was designed and implemented at the user-interface level. The output of the self-assessment is the definition of the missing digital and green skills that enable the definition of a customized retraining strategy.

1. Introduction

The digital revolution is introducing epochal changes and challenges. Companies that have invested in digital innovation in the last years are now in the need for an alignment of their internal competencies to maximize the return on investments, recognizing that they have to quickly adapt to new market conditions (Abele et al., 2015) and to adapt to a data-driven decision making approach (Tiwari and Raju, 2022). In view of this, the digitization has encouraged the conversion of human resource management to an ever more data driven activity (Pillai and Sivathanu, 2020), labeled as people analytics (Bonilla-Chaves and Palos-Sánchez, 2023; Green, 2017), work-force analytics (Simón and Ferreiro, 2018), human resources analytics (Marler et al., 2017; Rasmussen and Ulrich, 2015; Levenson, 2005), and human capital analytics (Andersen, 2017; Minbaeva, 2017, 2018; Levenson and Fink, 2017; Schiemann et al., 2018). Beyond the many nomenclatures, what is certain is the interdisciplinary nature of analytics applications, used to

analyse performance, engagement and career paths (Bersin et al., 2016). Among these, the topic of skills and job profiles foresight is ever more assuming a key role (WEF, 2016). In fact, the literature highlights not only the necessary integration of existing skills in professional profiles, but also the inevitable creation of new competences and jobs (Galati and Bigliardi, 2019) since the technological requirements demand specific skills to properly manage the digitalisation trends (Castelo-Branco et al., 2019; Mourtzis, 2018; Fareri et al., 2017; Fantoni et al., 2017; Frey and Osborne, 2017). Thus, rapid technological trends calls for frequent updates of jobs and skill taxonomies (ESCO,¹ O*NET²): even if they embody the state-of-the-art of professions and competencies, they are affected by several limitations (Handel, 2016) and their set of information struggles to stay aligned with the renewed requirements driven by digitization and should be integrated with external findings (Chiarlo et al., 2021; Malandri et al., 2021).

In this regard, the technical knowledge contained in documentations such as papers and patents remains widely unconsidered when trying to

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¹ Multilingual classification of Skills, Competences, Qualifications, and Occupations created by the European Commission. <https://ec.europa.eu/esco/portal/home>.

² Occupational Information Network.

predict competence demand, even if results are promising (Karwehl et al., 2022). Moreover, patent literature contains 80 % of the available technical information which cannot be found elsewhere (Geert, 2017) and there exists a direct correlation between patents and the impact of innovation, both for the predicting powers that they have (Daim et al., 2006; Campbell, 1983; Ernst, 1997; Liu and Shyu, 1997; Basberg, 1987) and the level of maturity of the technologies retrievable.

In parallel, in recent years the Industry sector was responsible for almost 55 % of the total global energy use, causing an ever more relevant global impact (IEA, 2016). Moreover, the world is struggling to achieve the sustainability objectives set out in the Paris Climate Agreement and none of the countries included in the assessment of (Sachs et al., 2022) succeeded, revealing strategies and actions of the governments insufficient also for European top performers. Even if many countries, in particular the OECD members, had shown commitment to meeting zero emissions, there is still a huge discrepancy between ambitions and reality (Sachs et al., 2022). Thus, Energy efficiency is increasingly considered a crucial theme and needs to be managed at all stages of the manufacturing process. However, the primary characteristic of Industry 4.0 is the digitisation of operations, which offers opportunities for energy saving and sustainability (Sachs et al., 2022; Wachnik et al., 2022; Oesterreich and Teuteberg, 2016) through the optimisation of or replacement of technologies, the application of ICT systems for energy efficiency management (Grabot and Schlegel, 2014) or adaptation in the business processes. The state of the art seems to focus on building models to assess the digital maturity of companies, considering instead the impact on the labor market as a hazy issue: frequently qualitative approaches are found, while quantitative skill assessments are less explored (Fareri et al., 2020). Notwithstanding, there is a growing skills gap among workers in the manufacturing industry, leading to a lack of skills to meet the needs for rapid technological development and sustainability conversion (Braun et al., 2022; Bukhvald et al., 2022; Luna-Arocas and Lara, 2020; Whysall et al., 2019).

To summarize, the urgent need to achieve sustainability objectives is evident, with the manufacturing sector playing a significant role in global emissions. However, key challenges lie in identifying the enabling key skills to properly manage new technologies acquisition and in the lack of tools and methodologies available to accurately assess the correspondent skills gap among manufacturing workers. Indeed, without comprehensive insight into the skills gap, it becomes difficult to identify areas where workers require upskilling or reskilling to effectively utilize new technologies for a sustainable manufacturing, while the definition of applications of frontier technologies calls for innovative methods to infer their enabling skills (Tiwari et al., 2022).

Given the above, the objective of this research is developing a tool capable of detecting the missing digital and green skills³ of workers, starting from a self-assessment of their current skill-set: the Energy Worker Profiler. For achieving the goal, the authors started by analyzing the trend of innovation of green technologies in patents. Then, the detection of relevant skills that enable the use of the previous technologies was performed linking the ESCO database with patent insights. Once the database of green and digital skills and jobs was defined, the algorithmic logic of the tool was designed and formalized. Finally, the Worker profiler was implemented as a web platform.

The present paper is structured as follows: first of all, a literature review concerning the value of digital and green competences for energy transition together with a framework of the current HR 4.0 solutions is presented; Secondly, the methodology adopted to reach the analysis objective is deeply described. In the end, the Worker Profiler is presented as well as conclusions and further developments.

Table 1
Literature review framework.

Section	Source	Time frame	Keywords
2.1	Scopus	2010–2023	“Digitization”; “Industry 4.0”; “Fourth industrial revolution”; “HRM”; “Human Resource Management”; “Talent Management”
2.2			“Energy efficiency”; “sustainability”; “green”; “manufacturing”; “production”; “skill”; “competence”
2.3			“Digital skill”; “soft skill”; “hard skill”; “green skill”; “assessment”; “evaluation”; “measure”; “tool”; “software”

2. Background

In this section, the authors present an extensive literature review that was built applying the boundaries presented in Table 1. The keywords used for each topic is reported, as well as the time frame selected and the data source. The authors chose to start presenting an overview of the impact of digitization on the HRM business function, which is affecting the way we manage, select, evaluate, and train people. Moreover, a focus of the key role of digital skills to enable energy efficiency and sustainability in manufacturing is presented. Finally, the state of art of skill profiling tools is reported, comparing the solutions with the one described in the present research work.

2.1. The impact of industrial revolutions on HRM

As the Industry 4.0 takes shape, the workforce needs to face an increased complexity of their daily tasks and are required to be flexible and to adapt to new (and challenging) working environments (Longo et al., 2017). Moreover, the recognition of people as the most valuable asset to invest on is widely stated in literature (Srimannarayana, 2010; Plessis and Fourie, 2016; Nienaber and Sewdass, 2016; Chattopadhyay et al., 2017) as well as the competitive advantage that they could bring (De Mauro et al., 2018). For these reasons, there is a growing scientific interest focused on the design and development of models, tools, practices that could help firms to assess the current skills of the workforce, to improve the evaluation of the human capital and to interact in a frictionless way with new technologies (Luna-Arocas and Lara, 2020; Whysall et al., 2019; Longo et al., 2017). In particular, the data driven culture conveyed by Industry 4.0, applied to HR departments, helps through HR analytics to achieve operational and strategic objectives (Huselid, 2018). In more detail, Human Resource analytics is defined as “A HR practice enabled by information technology that uses descriptive, visual, and statistical analyses of data related to HR processes, human capital, organizational performance, and external economic benchmarks to establish business impact and enable data-driven decision-making” (Marler and Boudreau, 2017). In other words, HR analytics is a set of methods and technologies that allows addressing several different issues, such as the evaluation of the performance metrics (Boyd & Gessner, 2013), the consciousness of worker well-being (Greasley & Thomas, 2020) and the assessment of their attitudes, behavior, talents (Shah et al., 2017). In particular, the evaluation of performance and competences based on data is fundamental to both increase efficiency (Garcia-Arroyo & Osca, 2019) and taking fact-based insights reducing subjectivity (Anshu and Tanuja, 2017). There are multiple definitions that have been adopted in the last 15 years, which tried to define the boundaries of the topic: extensive use of data and predictive models to drive decisions (Davenport & Harris, 2007), logical analysis that uses business data for reasoning (Fitz-enz, 2010), evidence based approach for managing people (Bassi et al., 2012; Boudreau and Jesuthasan, 2011), descriptive and visual analysis (Marler and Boudreau, 2017) and scientific and systematic methods to gauge the impact of Human capital management practices (Kryscynski et al., 2018; Van den Heuvel and Bondarouk, 2017). To summarize, the purposes are many as well as the

³ Attitudes and skills related to a transition to a circular economy.

methods that could be applied for exploiting data.

2.2. Digital skills to ensure energy efficiency

Not only digitization is affecting the way we work and live. In the last decade, climate change, global warming and the increasing quantity of carbon emissions have become an urgent and critical set of issues to be faced (Zhang et al., 2022). Moreover, there is a growing anthropogenic impact on elements that are considered the pillars of sustainability: economic, social and environmental (Lupi et al., 2022). In order to mitigate the phenomenon, it has become critical to limit energy consumption and improve energy efficiency, especially in manufacturing industries to face global warming, to cope with rising energy prices and to manage the increasing environmental awareness of customers (Bunse et al., 2011; May and Kiritsis, 2017; Liew et al., 2014). Furthermore, the increasing global energy demand together with the cost of fossil fuels and the downward trend in green energy prices have accelerated this transition (Arigliano et al., 2014). This interest is also evidenced by the development of 'Energy Efficiency First' as a key principle of the EU climate action plan (Dolge et al., 2021). Moreover, energy efficiency is considered a strong driver for meeting the 2030 climate targets since the attempts already made have not been enough to offset the impact of economic growth, which continues to drive energy consumption (European Commission, 2020). Moreover, improvements of energy efficiency in the Industrial sector could have a significant positive impact on reducing emissions (IEA, 2016; Bunse et al., 2011).

In this scenario, emerging technologies are essential drivers to move towards a sustainable industrial approach and gain relevant economic benefits (Lyu and Liu, 2021). In particular, Industry 4.0 enabling technologies (e.g., Artificial Intelligence (AI), Big Data analytics, the Internet of Things (IoT), robotics, blockchain and cloud computing) are considered crucial for realizing the transition. Moreover, the acquisition of Information and Communication Technologies (ICT) jointly with the creation of Cyber-Physical System (CPS) allow the implementation of an environmentally friendly production approach (Lupi et al., 2022). The blockchain technology helps reduce costs, limit delivery times and waste, while IoT, can contribute with data related to the transportation and processing of commercial waste, saving costs and time in recycling processes (Dongfang et al., 2022). Same reasoning could be done for Industry 5.0, based on three linked pillars: the central role of humans, the application of flexible technologies, and the sustainability of its technological solutions (Mourtzis et al., 2022). Thus, sustainability is inherent in the concept of Fifth Industrial revolution as well as the position of humans is ever more considered crucial (Romero and Stahre, 2021).

Since technology development both affects and helps energy intensive industries, the topic of identifying the digital skills which enable sustainable processes is becoming extremely strategic (Branca et al., 2022; Shamzuzoha et al., 2022). Organizations are required to be aligned with sustainability requirements, also acquiring and training people able to develop, manage, deploy IoT and know the potentiality of artificial intelligence to support green projects (Ogbeibu et al., 2022). Indeed, a new perspective of people management, the sustainable HRM, is increasingly relevant and focused on green performance of the workforce (Mirčetić et al., 2022). Furthermore, employees play an even more important role as promoters and recipients of human and organizational sustainability (De Stefano et al., 2017). Against this background, workers and their skills become a fundamental requirement for the transition to a green economy (ILO, 2011). More specifically, the relevant skills for sustainability are technical skills, knowledge, values and attitudes to support sustainable social, economic and environmental outcomes in business (Australian Green Skill Agreement, 2009). In particular, digital marketing and networking, business agility and renewable energy integrated into product manufacturing are currently considered to be the most relevant green skills (Manyati and Mutsau, 2021).

2.3. Skills profiling tools

Over the past few years, numerous systems, including web applications and apps, have been developed to facilitate HRM activities and to map the skill gap within the workforce to introduce AI solutions effectively (Morandini et al., 2023). Clear examples are recruitment systems, task allocation tools (Mourtzis et al., 2023), talent management platforms and, most of all, the use of quantitative mechanisms to assess individual capabilities with a more objective approach (Margherita, 2022; Giabelli et al., 2021). In particular, skills profiling tools play a crucial role in today's rapidly changing work landscape by providing valuable insights into the skills, competencies, and strengths of individual workers. These instruments are of paramount importance for several reasons. First of all, they enable organizations to effectively assess and match the skills of their workforce to specific job requirements. By identifying the strengths and areas for improvement of individual workers, organizations can strategically allocate resources, optimize team composition, and enhance overall productivity. Secondly, they facilitate personalized career development and training interventions. By understanding the skills and potential of workers and candidates, organizations can tailor training programs to address specific skill gaps and foster continuous learning (Cooke et al., 2021). Finally, by gaining a comprehensive understanding of the skills and capabilities of their workforce, organizations can proactively identify critical skills gaps.

The following table shows several state-of-art examples of profiling tools both from a business (the first three tools mentioned) and research perspective (Mattar et al., 2022) (Table 2).

While the previous tools have their strengths, there are certain areas where they may have limitations. One aspect which is frequently missing in those tools is the comprehensive coverage of skills. This narrow focus could limit the ability to provide a holistic view of an individual's capabilities and may not align with the evolving needs of industries and the job market (Yeoh, 2019). Additionally, the lack of forward-looking perspectives might be a gap in other tools. Without incorporating insights from emerging trends or innovations, these tools may not adequately address the future skill requirements of industries. One additional notable gap is the absence of a focus on green skills: no assessment tool focused on this topic raised from the literature review. Many existing tools primarily assess general skills or domain-specific competencies without specifically addressing the growing importance of sustainability and environmental considerations. This limitation can hinder individuals and organizations from effectively identifying and developing green skills, which are becoming increasingly essential in the context of sustainable practices.

In conclusion, while existing tools may have their strengths, it is crucial to consider the potential gaps they might have. These gaps could include the absence of standardized data sources, limited skill coverage and lack of forward-looking perspectives. Addressing these gaps can contribute to the development of more effective and comprehensive tools for skill profiling and development.

3. Methodology & results

In this section, we describe the methodology adopted to develop the database supporting the worker profiler and the tool itself, explaining the rationale with which it was built.

As we stated in the introduction, patents represent an excellent data source since 80 % of technical information is not retrievable elsewhere; additionally, patents provide a valuable overview of where innovation investments are focusing on (Daim et al., 2006). Analyzing patents allows for the identification and extraction of key technologies relevant to a specific domain or industry and by focusing on patents, a wide range of cutting-edge technologies can be captured, ensuring the inclusion of the latest advancements in the field. Even if Software is patented quite rarely, it can be if it is related to a hardware on which it has a physical

Table 2
Examples of profiling tools from a business and research perspective.

Tool	Assessment methodology	Data source or reference	Type of skills assessed	Use of analytics
Plum ^a ; Traitify ^b Pymetrics ^c	Behavioral assessments, gamified simulations Gamified neuroscience-based assessments Reflective Log	Five-Factor Personality Model Behavioral data, cognitive tests \	Cognitive, behavioral, soft skills Cognitive, social, emotional skills Motivation/transversal skills Digital skill	Predictive analytics, machine learning AI, machine learning Content Analysis Data visualization
Baruah et al., 2017				
The Digital Competence Wheel ^d Bartolomé et al. (2018); Calatayud et al. (2018) Kuzminska et al. (2019)	Self-Assessment 7-star Scale Self-assessment Likert Scale Scenario based and multiple choices questions Self-assessment Likert Scale	Digicomp 2.1 (Covello, 2010)		
Reddy et al., 2023			Digital skills	Exploratory factor analysis

^a <https://www.plum.io/plum-science>.

^b <https://www.traitify.com/>.

^c <https://www.pymetrics.ai/>.

^d <https://digital-competence.eu/dc/en/front/what-is-digital-competence/>.

effect, and this means that within the patents about the AI software systems also the hardware systems by which the software is implemented can be retrieved. Thus, Artificial intelligence applications can be patented, and patents are a source of very useful information about them.

At the same time, mapping these technologies to the corresponding skills is essential to exploit and implement new technologies. This mapping process involves analyzing the technical knowledge and competencies needed to understand, utilize, or innovate within the identified technologies. Thus, the designed process is based on exploiting patents, jointly with the International competence database ESCO,⁴ as the main source of standard skills and professional profiles, through the use of Text Mining techniques. The process is graphically summarized in Fig. 1.

Once the patents were analyzed and the main technologies retrieved, they were compared with ESCO skills through a semantic similarity analysis. Once the key competences were detected, the authors collected related job profiles as well, creating the knowledge-base behind the Worker profiler. Finally, the algorithm logic and the technical specification of the tool was defined and tool implemented. The next sections will explain in more detail each of the main activities of the process and the results obtained.

3.1. The patent analysis

As reasoned before, patent literature represents a unique source of technical knowledge. They contain information not findable elsewhere, giving an indication on where the innovation is focusing on, ensuring a high level of maturity and feasibility of technologies detectable (higher than those presented in, for example, non-patent articles and literature). The formal structure of patents allows the selection of documents focused on specific technologies of interest. In fact, patents describes the technical problem the invention is aimed to solve: this allows the detection of key aspects (characteristics, technologies, solutions, embodiments, components) that are more related to the object of the analysis, avoiding considering false positive signals or taking into account documents where a specific aspect is just mentioned. Furthermore, patents include detailed information on the development of

⁴ ESCO is a multilingual system that classifies occupations, skills, competences and qualifications relevant to the labor market in Europe. ESCO contains around 3000 occupations, the description of around 13,500 skills/knowledge and it provides links to qualifications that certify the acquisition of the competences. The occupation classification corresponds to ISCO-O8, which is the International Standard Classification of Occupations (International Labour Organisation, 2012).

technologies, and forecasting the introduction of a promising technology is a relevant opportunity for companies and countries. By observing the trend of filing patent applications (the number of applications filed over years), together with other parameters (main assignee or the current status of the application), it is possible to understand the maturity level of a technology and estimate its evolution in the next future. In addition, It is possible to extract the list of technologies that allow the resolution of a specific technical problem.

Patent trend analysis was developed following three steps shown in Fig. 2, using the European Patent Office database (Patstat Service) as the main data source. Each step is carefully described in the following sections.

3.1.1. Patent set definition

As mentioned before, the data source selected was the European Patent Office database, which contains more than 130 million documents belonging to all patent offices worldwide. The first step of patent analysis consisted on identifying the boundaries of the research. In particular we considered:

- The Manufacturing sectors of interest (Medical Device Manufacturing, Crankshaft Manufacturing, Tooling and Mould Production for Appliance)
- The objectives of sustainability and energy efficiency.

To detect relevant patents, a filtering strategy needed to be implemented. To achieve the goal, we used:

- IPC classes⁵ to select all and only the patents related to the sectors of interest
- CPC classes⁶ as a second filter to select all and only the patents related to sustainability.

The patent set was extracted using PatSearch (Zhang et al., 2018) considering two parameters fundamental in the world of Information Retrieval, called recall⁷ and precision,⁸ which allowed us to measure the quality of the patent set. The collected data were then analyzed and interpreted in order to generate an assessment of the technology's positioning relative to the state of the art. The analysis was focused on

⁵ <https://www.wipo.int/classifications/ipc/en/>.

⁶ <https://www.cooperativepatentclassification.org/cpcSchemeAndDefinition/table>.

⁷ Indicates the completeness of the set.

⁸ Estimate of the number of patents relevant to the subject matter present in the extracted patent set.

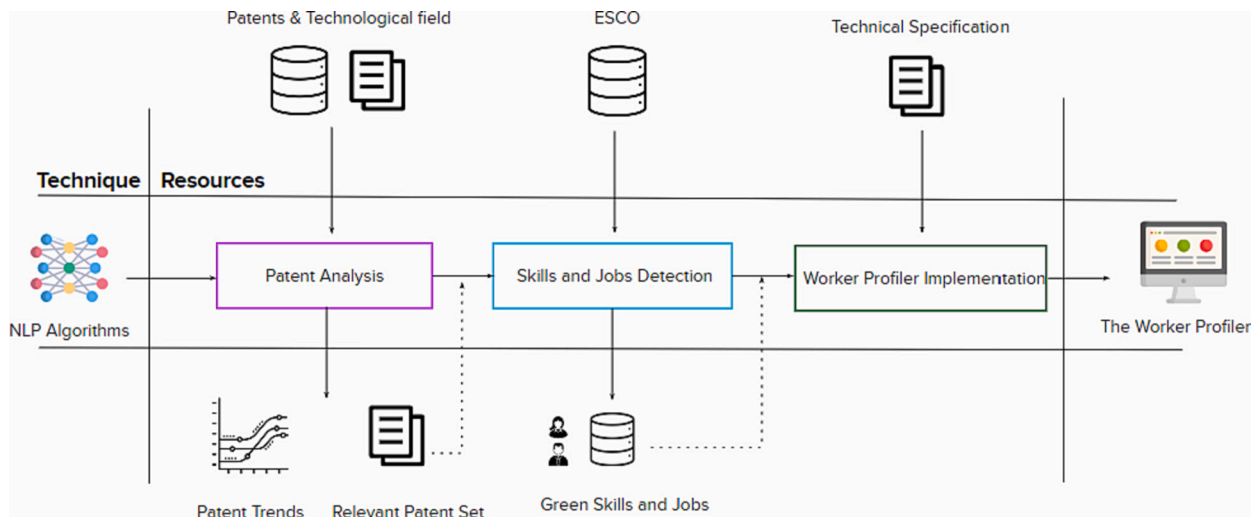


Fig. 1. Workflow of the adopted methodology. The central section shows the main process; the upper section shows the external resources used to carry on the analysis; the bottom section shows valuable intermediate outputs.

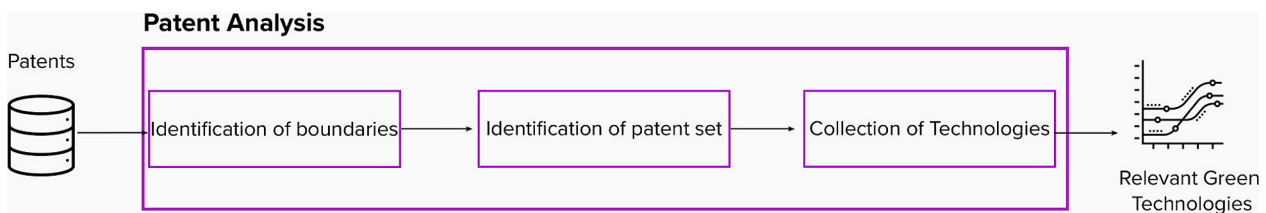


Fig. 2. Activities carried out to detect relevant green technologies through patent analysis.

one specific aspect: Temporal evolution of patent family⁹ filings. Indeed, the interpretation of the temporal trend allows hypotheses concerning the stage of technologies in their life cycle. In more detail, we leveraged Mann (2003) who defined five stages of the typical life cycle of a technology (Birth, Infancy, Growth, Maturity, Decline). According to this theory, the time distribution of the number of patent families filed annually is a good indicator for assessing a technological life cycle. In particular, the trend of patent family filings were compared with the Mann curve, identifying the ones that were at the beginning of stage 2, obtaining the list of relevant patent families (Fig. 3).

3.1.2. Technologies extraction

Once the relevant patent families were defined, the key technologies (and the phrases in which they were mentioned) needed to be extracted. The term technology has multiple definitions in scientific literature but we choose to adhere to (Puccetti et al., 2023): “a technical mean or in general a technical system created by human-kind through the application of knowledge and science, in order to solve a practical problem or perform a function”. Once the field was defined, we leveraged on a branch of Natural Language processing, Named Entity Recognition (NER). NER systems are widely used to extract general entities (e.g. objects, names, cities) but they are also applied to technological (Puccetti et al., 2023) and HR fields (Fareri et al., 2021; Cao et al., 2021). In this work, we applied a rule-based approach (Hearst, 1992), assigning to each term in the patent sentences its role (e.g., noun, adjective) and retrieving hypernym/hyponym relationships using Hearst (1992) fixed patterns. To detect only technologies, we selected hypernym which

contains the list of key terms provided by Puccetti et al. (2023)¹⁰, enlarged with synonyms obtained through Word2Vec. The technologies were manually revised by authors and clustered using detected hypernyms and the commonality of IPC classes of patents to which the technologies belonged, as drivers to detect similar concepts and to obtain a list with a homogeneous level of detail.

3.1.3. Results

The patent analysis allowed the identification of a global patent set composed of 22,402 patent families and 33 relevant clusters of technologies.

What seems evident from our analysis is that, in recent years, companies have focused their attention on energy savings; indeed, the majority of technologies retrieved focused on data collection, communication and management. Other results showed systems that utilize AI to identify and capture waste energy generated during manufacturing processes, to optimize energy consumption during manufacturing operations, to adapt lighting and heating, ventilation, and air conditioning settings based on environmental conditions, and predicting maintenance needs optimizing energy consumption. By combining these technologies, manufacturers can achieve significant energy savings, reduce costs, and enhance their sustainability efforts. An extract of the most relevant clusters of technologies is shown in Table 3.

3.2. From tech to skill

Starting from the list of clusters of technologies extracted from the patent analysis and the sentences in which they are contained, it is possible to infer the corresponding enabling competencies, exploiting a

⁹ European Patent Office (EPO): “A simple patent family is a collection of patent documents that are considered to cover a single invention. The technical content covered by the applications is considered to be identical. Members of a simple patent family will all have exactly the same priorities.”

¹⁰ Technology, machine, device, apparatus, mechanism, sensor, network, system, unit.

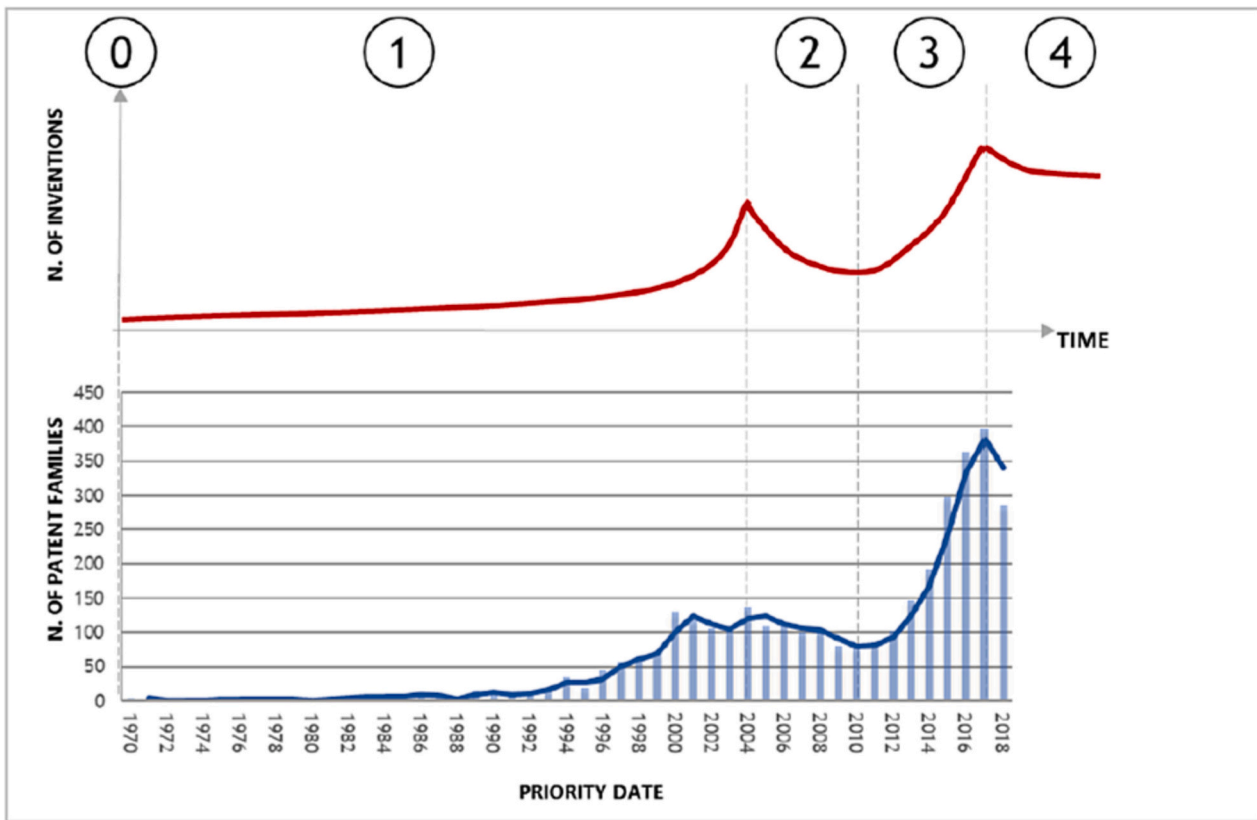


Fig. 3. Example of technological trend e Mann distribution of patents.

Table 3
Extract of technologies identified as key to energy efficiency.

Cluster of technology
Energy harvesting and recovery systems
Energy-efficient robotics and automation systems
Adaptive lighting and HVAC systems
Autonomous energy management systems
Energy storage devices
Predictive maintenance systems
...

Source: patents.

valuable data source: ESCO. To achieve the goal, the sentences were compared one-to-one with ESCO skills/knowledge through a semantic similarity algorithm based on BERT; only sentences with a similarity score greater than 0.7 were collected. Semantic similarity analysis was performed through a proprietary algorithm written in Python using PyTorch¹¹ and Torchvision.¹² For each patent sentence, only the best similarity score with ESCO skill was kept. The list of skills was manually revised by experts to filter duplicate and out-of-scope results. Experts removed all the skills that were not strictly related to a technology, as well as the ones that had been erroneously collected because of the ambiguity of meaning of some terms. The others were all considered as relevant for the research objective, validating the power of patents as a data source for innovation. A randomic extract of skills retrieved is shown in Table 4.

Finally, the job profiles mostly characterized by the previous set of skills were identified, developing the Worker Profiler database. The WP database consists of a list of 87 profiles and more than 300 key

Table 4
Extract of key skills.

Key skills
Advise on heating systems energy efficiency
Advise on utility consumption
Analyse energy consumption
Design air conditioning
Design solar energy systems
Implement machine learning
Data analysis for predictive modeling
Supervised and unsupervised learning methods
...

Source: ESCO.

competences between hard, soft, green and digital, of which 15 % belong to the latter category. An example of key energy efficiency professions, with a description of the purpose of the role, is shown in Table 5.

Once the relevant archetypes were defined, the authors proposed a classification into three macro-categories, obtained using both a top-down and a bottom-up approach. Following the top-down approach, the archetypes were labeled according to the macro-category declared in ESCO. Through the bottom-up approach, the authors validate the goodness of the previous result through a cluster analysis (Fig. 4) based on the semantic similarity between profiles composing each class. The result of the similarity analysis confirmed the top-down classification and represents a cross-validation process of our categorization. The final three classes of archetypes are Technicians-Operators, Managers-Consultants and Engineering professionals. The definition of the three classes are reported in Appendix 1.

¹¹ <https://pytorch.org>.

¹² <https://pytorch.org/vision/stable/index.html>.

Table 5
Example of key professions detected in international skills databases.

Job title	Job description
Energy engineers	Energy engineers design new, efficient and clean ways to produce, transform and distribute energy in order to improve environmental sustainability and energy efficiency. They derive energy from natural resources, such as oil or gas, or renewable and sustainable sources, such as wind or sun.
ICT managers for environmental sustainability	ICT managers for environmental sustainability know the legal framework for green ICT, understand the role of ICT network configurations in the economy and distribution of energy resources, and assess the carbon footprint impact of each ICT resource in the organization's network. They plan and manage the implementation of environmental strategies for ICT networks and systems, conducting applied research, developing organizational policies and devising strategies to achieve sustainability goals. They ensure that the entire organization uses ICT resources in the most environmentally friendly way possible.
Sustainability managers	Sustainability managers are responsible for ensuring the sustainability of business processes. They assist in the development and implementation of plans and measures to ensure that production processes and products comply with certain environmental and social responsibility standards and monitor the implementation of sustainability strategies within the company's supply chain and business process and report on the results. They analyse issues concerning production processes, material use, waste reduction, energy efficiency and product traceability in order to improve environmental and social impact and integrate sustainability aspects into the corporate culture.

3.3. The worker profiler

The Worker Profiler¹³ is a web-app that enables the user to perform a self-assessment of their own skills, with a particular focus on green skills (and skills gap). The list of green skills included in the Worker profiler is reported in Appendix 3. The software is also able to identify, starting from the selection of one's profession, the profiles most akin to that of the user in terms of skills currently possessed, in order to highlight (prospective) activities of effective job rotation. The expected users are both blue and white collar job profiles, as reported in Appendix 1, with a specific focus on the ones impacted by the introduction of new technologies. The platform was designed and developed following minimalist UI principles, with the objective of having a clean looking, multi-device and multi-platform UI, fully working in PCs but also in Tablets and Mobile devices. For these reasons we relied on responsive Bootstrap code augmented with some ad-hoc CSS code, carefully selected JavaScript libraries and a collection of SVG Icons. The application also takes into account the privacy of workers, allowing them to control and manage all their assessments and data.

The tool, which has the appearance of a questionnaire, was built taking the database of skills and professions described above as the main data source. Considering the user-experience (Fig. 5), the worker is asked to select the professional profile with which he or she best identifies from the list of 87 professional archetypes. Subsequently, the users will choose the hard skills, digital skills, and soft skills they currently possess. Finally, the tool calculates the distance between the answers and the ideal skill set of the profile of interest (Fig. 6), providing also information about soft skills to improve or maintain for the current occupation (Fig. 7) and offering the user a detailed assessment of those (hard, digital, green) to be acquired and evidence of the three

professional profiles most similar to it. The tool is user-friendly and useful to propose ad hoc-training experience and gives a data-driven indication to realize an effective job rotation.

3.4. Pilot tests

Once the first release of the tools was completed, a pilot test for the tool was conducted considering three parameters: usability, time for completion and completeness of the content.

3.4.1. Test participants

Four pilot enterprises from different manufacturing sectors were selected to participate in the test. A representative sample of four workers from each company, belonging to the same job profile category, was selected for testing the self-assessment tool. The selection of professional profile categories to be evaluated using the tool was based on the statements provided by individual companies regarding the occupations most affected by the integration of new technologies and the shift towards environmentally sustainable practices. Table 6 provides a summary of the participants and the manufacturing sectors to which their respective firms belong.

3.4.2. Test process

The tool test was conducted independently by the participants following a brief description of the tool's functionality, value, and expected outcomes. The test users were not guided in conducting the assessment, to evaluate the usability and intuitiveness of the tool. Users were requested to log the time taken to complete the survey and to note any observations concerning usability and outcomes received.

3.4.3. Test results

The main results of the pilot tests are reported in Table 7.

Overall, the self-assessment tool was perceived as highly user-friendly by the participants. Its intuitive interface and clear instructions facilitated easy completion of the assessment. The tool's visualizations and graphical representations were particularly appreciated, as they provided a concise overview of the skill gaps. However, the study revealed certain criticalities related to the content of the tool and to the absence of definition of specific concepts (such as "soft skill" definitions) that may confuse the user. Participants noted that certain industry-specific knowledge and emerging energy-efficient technologies were missing from the assessment. These observations emphasized the need to update and expand the underlying database to ensure the tool's relevance in a rapidly evolving manufacturing landscape. Based on these findings, the tool developers initiated a process of continuous improvement, collaborating with industry experts and practitioners to ensure the inclusion of the latest industry-specific knowledge and emerging energy-efficient technologies.

To conclude, this first round of pilot tests demonstrated the promising potential of the self-assessment tool in detecting skill gaps in energy efficiency for manufacturing workers. While the tool was well-received for its user-friendly interface, the study emphasized the need for periodic updates to enhance the content and ensure its relevance in a rapidly changing industry.

4. Discussion & outlook

Realizing energy efficiency in manufacturing is a key component for companies looking to reduce their operational costs and maintain a sustainable product. To achieve this, it is essential to first identify the digital and green skill gaps that exist within the manufacturing environment. Self-assessment tools enable companies to do this effectively. A self-assessment tool is a tool used to identify gaps in knowledge and skills for a particular purpose. In the case of energy efficiency in manufacturing, this tool can be used to identify the digital and green skill gaps that need to be addressed in order to reach the desired level of

¹³ The tool is available here: <https://denim.r2m.cloud/register.html>.

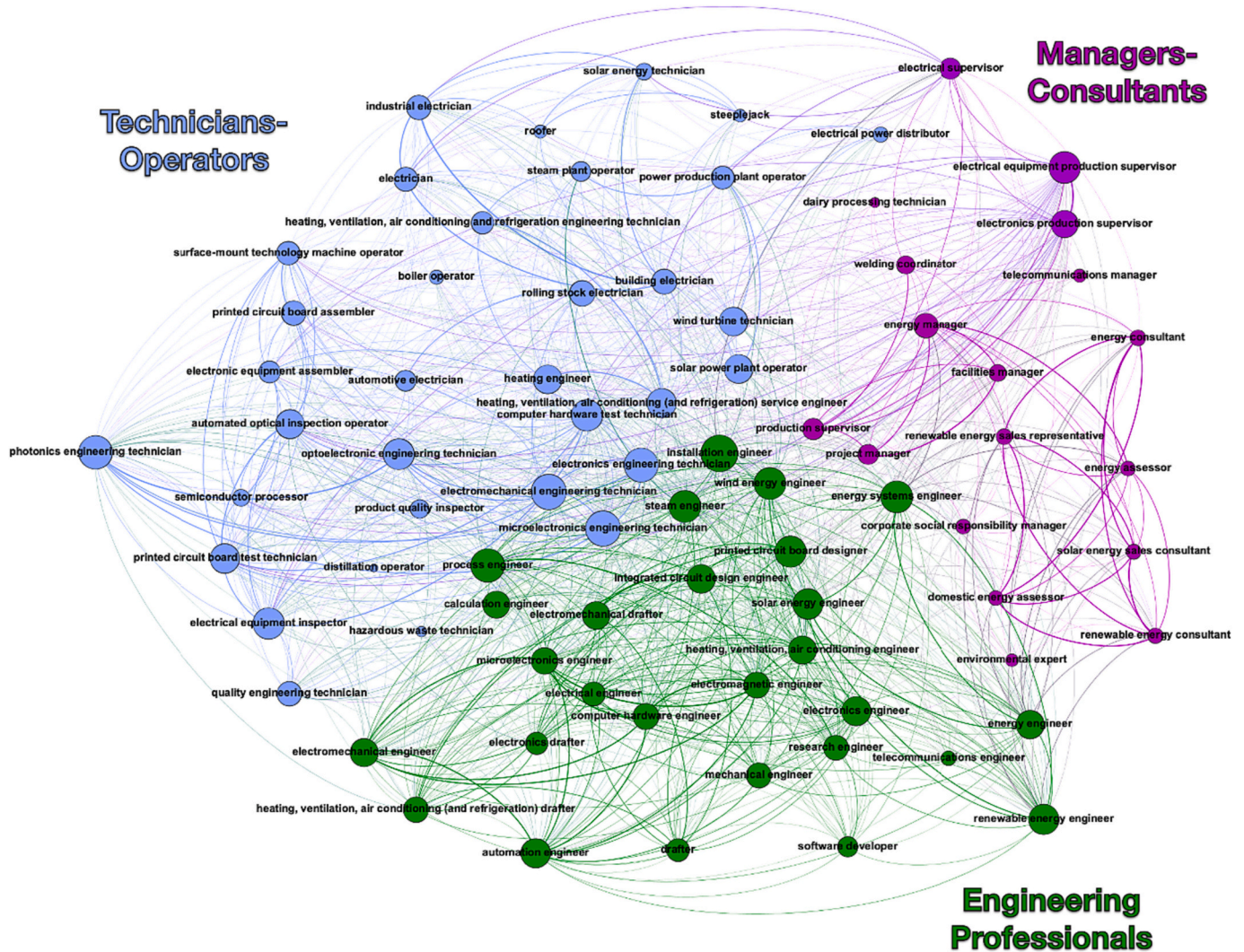


Fig. 4. Data-driven approach to detect cluster of jobs.

efficiency. Such a tool offers a number of benefits. Firstly, it is easy to deploy, since it can be accessed by anyone in the organization and requires no setup. This makes it convenient for managers and employees to use, as they can access the tool whenever they need it. Furthermore, it can be tailored to the specific requirements of the organization, enabling them to identify the gaps in the most efficient manner. Secondly, a self-assessment tool is cost-effective. It is often much cheaper than other methods of assessing skill gaps, such as using external consultants or conducting surveys. This makes it an attractive option for companies looking to reduce their operational costs. Finally, a self-assessment tool can provide more accurate and reliable results than other methods. This is because it can take into account the individual responses of each user, as well as the wider context of the organization. This can help to identify any potential issues or areas where improvement may be needed. Thus, the worker profiler tool can assist organizations in designing and implementing energy efficiency programs that are tailored to the individual needs of the workers.

Although a self-assessment tool is an invaluable tool for organizations looking to identify their digital and green skill gaps, it is important to note that there are some limitations. For example, the results may not be completely accurate as the tool is reliant on the responses of the users. This can lead to a bias in the results if the users are not being completely honest, or if they are not familiar with the concepts being tested. Furthermore, the tool may not be able to measure certain aspects of the skill gap, such as the level of knowledge or experience of the users. In

addition, the tool may not be able to take into account the context of the organization, such as its size, culture, and goals. This means that the results may not accurately reflect the true state of the organization's digital and green skill gaps.

Despite the limitations, the tool proposed in this article has distinctive value compared to the state of art, both from an academic and from a business perspective.

The degree of innovation of our tool lies in several key aspects:

- Innovative approach: the database hidden behind the worker profiler was built through frontier methodologies, exploiting patents as the main data source to detect key green technologies. This approach allowed the authors to identify key skills and job profiles from International competence databases and to integrate the latter with new technological skills that were missing.
- Holistic Approach: Unlike many existing tools that focus solely on assessing technical knowledge or specific skill sets, our tool takes a comprehensive approach. It evaluates not only technical competencies but also behavioral and contextual skills necessary for energy efficiency in manufacturing. This holistic assessment provides a more accurate and complete picture of the worker's skill gap.
- High precision and tailoring: Our tool goes beyond generic assessments, taking into account the specific needs and requirements of the manufacturing industry, including skills and job profiles that cover

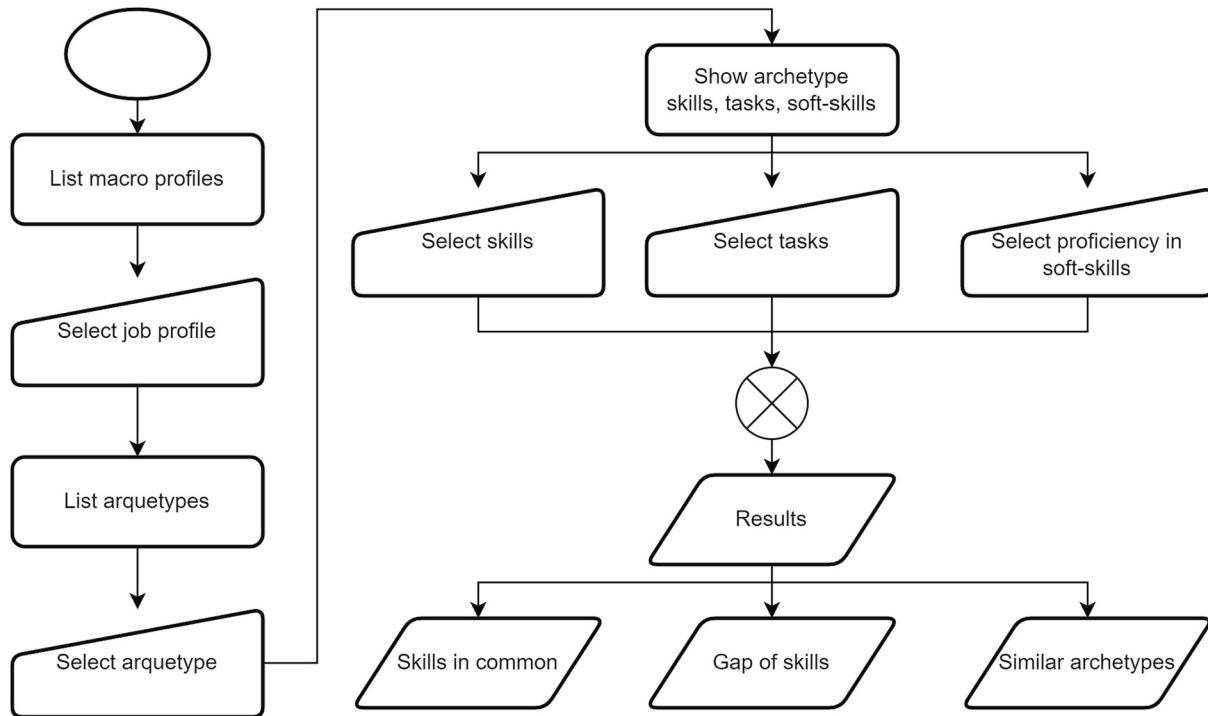


Fig. 5. Flowchart of the worker profiler.

TASKS

Selected	Suggested
<ul style="list-style-type: none"> • Adjust engineering designs • Adjust voltage • Analyse energy consumption • Approve engineering design • Assess environmental impact • Calculate solar panel orientation • Design electric power systems • Maintain concentrated solar power systems • Maintain solar energy systems • Manage environmental impact of operations • Perform scientific research 	<ul style="list-style-type: none"> • Provide information on solar panels • Provide information on wind turbines • Promote environmental awareness • Advise on environmental remediation • Identify energy needs • Create designs for pipeline engineering • Use technical drawing software • Promote sustainable energy • Design solar energy systems

Fig. 6. Example of worker profiler outputs - task selected and task suggested (i.e. skills gap).

different sectors, processes, and organizational contexts and, simultaneously, are key actors for sustainability in manufacturing.

- **Training Solution Integration:** In contrast to existing tools that focus solely on identifying skill gaps, our tool goes a step further by proposing targeted training solutions. It not only highlights the areas where workers lack proficiency but also provides a roadmap for upskilling and reskilling. This integration of assessment and training recommendation streamlines the entire process, enabling organizations to address skill gaps more effectively.
- **Continuous improvement:** Our tool incorporates the possibility to register the assessments and provide an overview to HR managers that could test workers multiple times to understand what changed after the training activities. It doesn't treat skill assessment as a one-time event but rather as an ongoing process. This feedback loop ensures that the training solution remains relevant and responsive to the evolving needs of the workers and the industry.

- **Analytics and Data Visualization:** Leveraging analytics and data visualization techniques, our tool provides in-depth insights into skill gaps. It presents the assessment results in a visually appealing and easily understandable format, allowing organizations to identify priority areas for intervention. The tool's ability to present data in a user-friendly manner sets it apart from existing tools that often lack sophisticated visualization capabilities.

By combining these innovative features, our self-assessment tool represents a significant advancement in the field of energy efficiency skill assessment and training. Its comprehensive approach, customization, integration of training solutions, real-time monitoring, and analytics contribute to a more efficient, targeted, and impactful skill gap detection and resolution process.

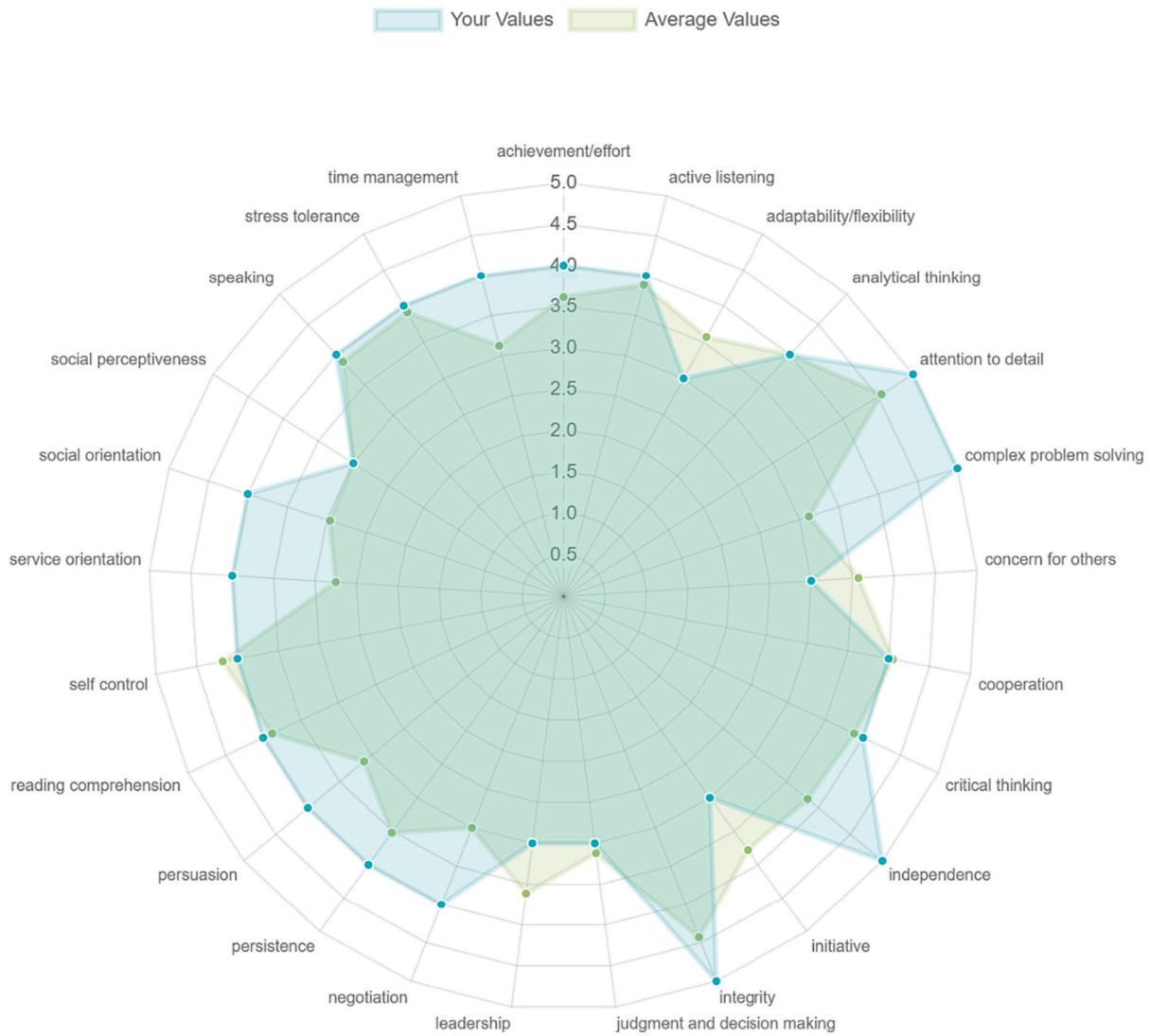


Fig. 7. Soft skill comparison chart.

Table 6
Test users and related companies' description.

Pilot ID	Pilot sector	#N. of test users	Job profile categories
1	Medical devices/life science	4	Energy engineers
2	Steel manufacturing & forging	4	Project managers
3	Tool manufacturing	4	Automation engineers
4	Composite components manufacturing	4	Mechanical engineers

5. Conclusions

Due to the increasing relevance of energy efficiency in manufacturing, designing, managing and maintaining production models with reduced environmental impact, fully adopting enabling technologies, and operationalizing investments made in new digital technologies is essential and requires a broad and complex transformation of the skills of the workers. In this context, Artificial Intelligence and tools that rely on data-driven approaches can be useful for all companies engaged in this transformation. Artificial Intelligence helps automate steps and analyses (such as the so-called “skill gap” analysis, i. e., measuring the distance between current and ideal skills) by

Table 7
Results of pilot tests - average completion time and example of comments received.

Pilot ID	Average completion time	Usability and content comments
1	10 Minutes	The tool provides standard job positions, perhaps for operators a more detailed solution is needed. Add an expected time to complete at the beginning of the questionnaire.
2	13 Minutes	Digital skills in the questionnaire are general, more specific ones are not listed (for example, the use of Autodesk Autocad is present but there is not any specific CAD tool such as Katia, Solidworks)
3	9 Minutes	Provide a brief description of the soft skills with possibly a concrete example (“what’s the meaning of active listening?”)
4	12 Minutes	Broaden the choice of digital skills (Alphacam, Java, Snape...)

representing an assessment tool, or self-assessment, within everyone’s reach. In this article we present the Energy Worker Profiler, a software designed to map the skills currently possessed by workers, identifying the mismatch with those they should ideally possess in order to meet the renewed demands that digital innovation and environmental protection

impose. The Worker Profiler was built starting from the detection of key technologies and skills for the area of interest (in this case, adoption of digital technologies for efficient energy management in industry), identifying those with distinctly increasing trends and identifying green and digital skills and professions that enable them. In more detail, starting from four sectors of interest and four different digitization and sustainability objectives, a patent analysis was conducted to detect the technologies of interest with a marked increasing trend. After that, semantic similarity algorithms were applied to the International Competence Database (ESCO), to detect a set of enabling skills and related job profiles. The number of relevant job profiles retrieved was 87 and the relevant skills more than 300. The knowledge base was then taken as input for the semi-automatic creation of a questionnaire to evaluate the current skills of workers and to assess the key green e digital gaps. After that, a User-interface was developed to make the Worker Profiler accessible. The output of the self-assessment is the detection of the 3 archetypes the worker embodies the most, and the differences between the skills they currently possess and the ones that they need to acquire. The latter represents the starting point to detect ad hoc training courses and to define the customized up-skilling strategy. To conclude, the assessment process aims to be data-driven, efficient and easy to replicate in other contexts and industrial sectors and will offer evidence-based approaches to enhance the maturity and workforce skills towards digital and sustainable factories of the future.

Appendix 1. Job macro-classes

Table A1

Archetypes's macro-classes and their definitions.

Macro-class	Definition
Technicians-operators	Operators & technicians perform technical tasks connected with research and operational methods in science and engineering. They operate and monitor plants and adjust and maintain processing units and equipment. They supervise and control technical and operational aspects of manufacturing, construction and other engineering operations.
Engineering professionals	Engineering professionals design, plan and organize the testing, construction, installation and maintenance of structures, machines and their components, and production systems and plants; and plan production schedules and work procedures to ensure that engineering projects are undertaken safely, efficiently and in a cost-effective manner.
Managers-consultants	Managers plan, direct, coordinate and evaluate the overall activities of enterprises, governments and other organizations, or of organizational units within them, and formulate and review their policies, laws, rules and regulations. Consultants provide advice on how to optimize the use of existing tools and systems, make recommendations for the development and implementation of a business project or technological solution and contribute to project definitions.

Appendix 2. Implementation

In this appendix we will detail some of the most representative software and hardware tools used in this research work. At the platform level we rely on Debian GNU/Linux operating system machines on which we run Docker as a tool to package and containerize the web application and manage its deployment. Initially the cloud part of the solution is being self-hosted in our servers but thanks to containers and to the use of well-known widely tested tools, we can deploy later the operational prototype to any IaaS (e.g.: Azure or AWS Cloud Computing Services) when the volume of users and scalability needs demand it.

On this platform at the application level we developed the web application in Python, using the microframework Flask, employing a MVC (Model - View - Controller) software architecture pattern. For the model we benefit from SQLAlchemy as an Object Relational Mapper and SQL kit, relying on a PostgreSQL database. As View, we used Jinja2 templates, with which we developed a user interface based on HTML, Bootstrap and JavaScript. Finally, access to the application is provided by the WSGI HTTP Server Gunicorn, together with the NGINX web server.

In turn, the research, data collection and processing was carried out using data analysis software, one for the execution of the patent analysis (PatSearch) and other for the extraction of key skills related to patent technologies (Python, using PyTorch¹⁴ and Torchvision¹⁵).

CRedit authorship contribution statement

Silvia Fareri: Conceptualization, Methodology, Writing – original draft, Project administration. **Riccardo Apreda:** Supervision, Project administration, Writing – review & editing. **Valentina Mulas:** Formal analysis, Data curation. **Ruben Alonso:** Software.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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Data availability

Data will be made available on request.

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¹⁴ <https://pytorch.org>.

¹⁵ <https://pytorch.org/vision/stable/index.html>.

Appendix 3. The green skills

Table A2

The list of green skills contained in the worker profiler.

The green skills
Adapt energy distribution schedules
Advise on heating systems energy efficiency
Advise on pollution prevention
Advise on potential safety hazards concerning heating systems
Advise on utility consumption
Analyse energy consumption
Analyse energy market trends
Analyse environmental data
Analyse production processes for improvement
Avoid contamination
Carry out energy management of facilities
Carry out environmental audits
Check durability of materials
Collect industrial waste
Conduct energy audit
Conduct environmental surveys
Conduct quality control analysis
Coordinate electricity generation
Define manufacturing quality criteria
Define quality standards
Design air conditioning
Design solar energy systems
Develop electricity distribution schedule
Develop environmental remediation strategies
Develop hazardous waste management strategies
Develop strategies for electricity contingencies
Dispose of hazardous waste
Ensure compliance with electricity distribution schedule
Ensure compliance with environmental legislation
Environmental engineering
Identify energy needs
Identify hazards in the workplace
Industrial heating systems
Install concentrated solar power systems
Maintain photovoltaic systems
Measure pollution
Mitigate waste of resources
Monitor environmental parameters
Monitor manufacturing quality standards
Operate recycling processing equipment
Promote environmental awareness
Promote sustainability
Promote sustainable energy
Promote sustainable management
Remove contaminants
Remove contaminated materials
Use thermal management

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