

Skills in Industry 5.0: Which Ones Really Matter?

Luca Carminati^{1*} , Roberto Sala¹ , Fabiana Pirola¹ , Rossella Pozzi² ,
Mohammad Hossein Dehbozorgi³ , Monica Rossi³ 

¹Dipartimento di Ingegneria Gestionale dell'Informazione e della Produzione. University of Bergamo. Dalmine (BG) (Italy)

²Dipartimento di Ingegneria Gestionale dell'Informazione e della Produzione. LIUC University Carlo Cattaneo. Castellanza (VA) (Italy)

³Dipartimento di Ingegneria Gestionale, Polytechnic University of Milan. Milano (MI) (Italy)

*Corresponding author: luca.carminati@unibg.it, roberto.sala@unibg.it

fabiana.pirola@unibg.it, rpozzi@liuc.it, mohammadhossein.dehbozorgi@polimi.it, monica.rossi@polimi.it

Received: November 2025

Accepted: July 2026

Abstract:

Purpose: This study aims to identify and prioritize the key skills required to support the transition toward Industry 5.0. It investigates both technical and non-technical competencies, with the hypothesis that soft skills are increasingly critical alongside traditional engineering expertise.

Design/methodology/approach: A comprehensive literature review was conducted to identify relevant skills associated with Industry 5.0. These were then prioritized by a panel of experts using the MaxDiff methodology. In addition, a network analysis of academic literature was performed to explore interconnections among the identified skills.

Findings: Findings reveal that while technical and engineering skills remain fundamental, there is a strong need to complement them with soft skills such as flexibility, change management, problem solving, critical thinking, leadership, communication, and teamwork within interdisciplinary contexts.

Research limitations: This study relies on the perceptions of a panel of experts involved in the MaxDiff analysis, which may reflect specific geographical or sectoral biases. Future research could expand the sample size and validate the prioritized skills across different industrial sectors to generalize the findings.

Practical implications: The findings offer actionable guidance for HR managers and industrial leaders in redefining job profiles and recruitment strategies, highlighting the urgency of prioritizing soft skills alongside technical expertise. Furthermore, the study could help Higher Education Institutions and Vocational Education and Training institutions in redesigning engineering curricula.

Originality/value: The study provides an integrated overview of the competencies most relevant for Industry 5.0, emphasizing the importance of combining technical proficiency with human-centred capabilities. The results offer valuable insights for future research, educational program design, and workforce development strategies.

Keywords: skills, sustainability, human-centricity, resilience, digitalization, maxdiff

To cite this article:

Carminati, L., Sala, R., Pirola, F., Pozzi, R., Dehbozorgi, M. H., & Rossi, M. (2026). Skills in Industry 5.0: Which ones really matter?. *Journal of Industrial Engineering and Management*, 19(3), 508–541.
<https://doi.org/10.3926/jiem.9264>

1. Introduction

Achieving the objectives often associated with the emerging concept of Industry 5.0, which include fostering sustainability, enhancing human-centricity, and increasing resilience in industrial processes, requires significant interventions to modify the organizational structure of the companies (Huang et al., 2022). The organizational structure and processes must become more flexible and resilient, while ensuring efficient and environmentally sustainable processes (European Commission. Directorate General for Research and Innovation., 2021; Sindhwani et al., 2022). In this evolving framework, the human element is increasingly brought to the center, considering their needs, values, and characteristics as critical business objectives (Nahavandi, 2019).

For this proposed transition to be successful, it is necessary not only to strategically acquire employees with the skills required to support resilient, sustainable, and technologically advanced processes, but also to upskill existing employees (Kolade & Owoseni, 2022; Nahavandi, 2019). With new educational needs arising, it is essential that Higher Education Institutions and Vocational Education and Training institutions adapt their proposed curricula to evolving market demands, thus ensuring qualified and highly competitive personnel (Carminati et al., 2024; Fleming et al., 2024; Gürdür Broo et al., 2022; Martin et al., 2022). While several competency frameworks have emerged in recent years to address these challenges, the academic landscape still lacks a comprehensive and integrated view of skills related to the key pillars conceptualized under the Industry 5.0 umbrella: human-centricity, resilience, sustainability. Although not directly associated with this concept, the digital pillar should also be included as it is widely argued to serve as the fundamental basis of the other Industry 5.0 pillars. Considering these four pillars, today's industrial environment frequently requires companies to develop cross-cutting skills (Hofmann Trevisan et al., 2024; Ming et al., 2025).

1.1. Theoretical Background and Related Works

To adequately ground this study within contemporary academic discourse, it is necessary to examine the ongoing theoretical debate surrounding the transition from Industry 4.0 to the proposed Industry 5.0 framework. While Industry 4.0 focused fundamentally on technological optimization, cyber-physical systems, and digital efficiency, the concept of Industry 5.0 has been introduced, primarily through policy frameworks by the European Commission, as a conceptual evolution rather than a technological replacement (European Commission. Directorate General for Research and Innovation., 2021). It proposes a socio-technical perspective that attempts to shift the focus from a techno-centric drive toward a paradigm, where human-centricity, sustainability, and resilience should complement existing digital infrastructures.

However, as highlighted by current critical literature, Industry 5.0 cannot yet be considered a fully stabilized or universally accepted paradigm; it remains an emerging and heavily debated concept within academia. Scholars frequently argue whether it represents a genuinely new industrial revolution or merely an ideological extension of Industry 4.0 designed to address its socio-environmental shortcomings. Because this conceptual boundary is still fluid, evaluating modern professional requirements cannot rely on rigid, pre-established taxonomies. Instead, it requires an exploratory and integrated investigation into how technical skills interact with these newly debated socio-technical dimensions. Within this theoretical scope, several authors have recently attempted to draft dedicated competency frameworks aligned with the principles of Industry 5.0 (Gustavsson et al., 2024; Mattsson & Kurdve, 2024; Pinto et al., 2025; Skripnik et al., 2023; Vitti et al., 2025), a critical review reveals that these models generally fall into three distinct conceptual limitations: context-dependency, operational hyper-specialization, or single-pillar fragmentation.

The first limitation concerns frameworks that are highly context-dependent or focused on training delivery rather than taxonomy design. For instance, the model developed by Vitti et al. (2025) targets circular economy education; although it effectively introduces human-centric and resilience-oriented traits, its architecture is structurally interconnected to sustainability, lacking the generalizable breadth needed for broader industrial applications. Similarly, Pinto et al. (2025) focus on upskilling paths within smart manufacturing, but their work is primarily aimed at optimizing flexible learning models and training content, rather than providing a formalized and structured classification of individual skills.

A second body of literature suffers from operational hyper-specialization, restricting the applicability of the skillsets to specific shop-floor figures or temporary situational crises. This is evident in the framework by Skripnik et al. (2023), which targets assembly operators. While operationally granular, such a narrow scope cannot support cross-functional workforce strategies across different organizational layers. In a similar way, Mattsson and Kurdve (2024) explore the competencies of the “Operator 5.0” during emergency production shifts; however, they treat resilience as a reactive, contingency-driven tool for crisis management rather than a proactive, transversal capability embedded in long-term human resource development.

Finally, a third stream of research exhibits single-pillar fragmentation, isolating technological proficiency from broader socio-environmental goals. A clear example is the study by Gustavsson et al. (2024), which effectively maps digital and data-driven skills through collaborative expert networks but leaves the interconnected human-centered, resilient, and green dimensions outside its analytical boundaries.

1.2. Research Gap and Objectives

By empirically examining how digital, sustainable, resilient, and human-centered skills interact and complement one another, this study moves beyond fragmented perspectives to offer an integrated framework for contemporary industrial organizations. This makes it essential not only to identify which skills relate to each pillar, but how these skills might be interconnected. Understanding these relationships could lead to more effective training and workforce development strategies that leverage synergies across domains. In order to fill this gap, the following research questions have been defined:

RQ1: What are the core skills associated with the key pillars debated within Industry 5.0: human-centricity, resilience, sustainability, and digital?

RQ2: What are the synergies and interdependencies among skills related to the human-centric, resilient, sustainable, and digital pillars, and how can understanding these relationships inform more effective workforce upskilling strategies?

To answer these questions, first, a systematic literature analysis was conducted to identify the key skills for this evolving industrial context. This literature analysis has been supplemented by a Max-Diff study, which was carried out with a panel of industry experts. The purpose of the study was to evaluate the perceived relevance of the skills that emerged from the literature on operational practice. Furthermore, a network analysis was conducted on the competency set derived from the literature. This analysis yielded a visual and structural overview of the manner in which distinct skills are discussed in the academic discourse. Additionally, it examined how these relationships are reflected in practical applications.

This brief introduction is followed by a detailed description of the methodology in Section 2, covering both the systematic literature analysis (2.1) and the Max-Diff study (2.2). Section 3 presents our results, including skills extracted from the literature (3.1), their grouping for submission to industrial participants (3.2), and their categorization to enhance understanding (3.3). Section 4 discusses the findings, examining both the Max-Diff study results (4.1) and the network analysis of identified skills (4.2). Finally, Section 5 concludes by summarizing the main steps and results, while addressing limitations and suggesting directions for future research.

2. Methodology

The study's methodology consists of two parts: a systematic literature review to identify skills (Sub-Section 2.1) and a Max-Diff study to rank them (Sub-Section 2.2).

2.1. Systematic Literature Review

A systematic literature review was conducted following PRISMA methodology for reliability and transparency (Page et al., 2021). The review began late 2024 using the Scopus database, chosen for its comprehensive coverage of articles on skills needed in the new industrial context. The search query entered into the database was structured around the themes of Industry 5.0 and Industry 4.0, the latter linked to at least one of the three main components of Industry 5.0 - resilience, sustainability, and human-centricity - and the topic of competencies, skills, and capabilities. The query was formulated as follows:

((TITLE-ABS-KEY ("Industr* 5.0" OR "I5.0" OR "manufactur* 5.0" OR "technolog* 5.0" OR "Operator* 5.0") OR (TITLE-ABS-KEY ("Industr* 4.0" OR "I4.0" OR "manufactur* 4.0" OR "technolog* 4.0" OR "Operator* 4.0") AND TITLE-ABS-KEY (resilien* OR sustainab* OR "Human cent*" OR "Human-Cent*"))) AND TITLE-ABS-KEY (*skill* OR competenc* OR abilit* OR knowledg* OR capabilit*))

To ensure the rigor and reproducibility of the systematic literature review, the inclusion of specific technical terms representing single enabling technologies (such as Artificial Intelligence, Internet of Things, or Robotics) within the search string was intentionally avoided. Preliminary exploratory tests demonstrated that appending specific technological keywords via restrictive Boolean operators (AND) excessively constrained the final document pool, thereby omitting comprehensive competency frameworks that address general manufacturing upskilling. Conversely, introducing these technological terms via additive operators (OR) generated substantial methodological noise, retrieving a vast body of strictly engineering and out-of-scope literature irrelevant to the purpose of the study. Consequently, the search strategy was purposefully designed to target the conceptual intersection between the broader industrial paradigms and workforce capabilities. By requiring the presence of core transitional pillars (resilien*, *sustainab*, human-cent*) alongside Industry 4.0 and Industry 5.0 terms, the query successfully captured relevant literature discussing how workforce requirements evolve during this transition.

The query input into the database returned 2162 documents. It was therefore decided to add filters to refine the search for only relevant documents:

- Timespan: From 2018
- Pub-stage: Final
- Type: Article or Conference Paper
- Language: English
- Subject Area: Engineering, Computer Science, Business Management and Accounting, Social Sciences, Environmental Science, Decision Sciences, Multidisciplinary.

Filtering yielded 1414 articles, which were screened in three steps: title review, abstract analysis, and full-text assessment. The following inclusion criteria were applied to select articles:

- Focus on Industry 5.0 and/or its main components and objectives (resilience, sustainability, and human-centricity).
- Applicability of observations to the manufacturing context.
- Clear definition of the importance of these skills for the new industrial context.

The title screening reduced relevant articles to 251. Many were excluded because they only mentioned skills peripherally rather than as a central focus. Industry 5.0 requires redefining worker skills (Adel, 2022; Oeij et al., 2024), but many papers only briefly mention this need without deeper exploration. For example, papers discussing manufacturing sustainability might mention operators upskills as future work without substantial analysis. Abstract screening further reduced potential documents to 60, and full-text review yielded a final set of 28 articles. Figure 1 summarizes this selection process.

The extraction and labeling of skills from the final sample of 28 articles followed a rigorous and formalized content analysis process. The initial data extraction was conducted by one researcher, who extrapolated each explicit mention of skills from the selected literature. To ensure internal validity and handle near-synonymy or linguistic redundancies (e.g., matching “collaborative capabilities” with “teamwork”), an iterative consolidation procedure was executed. This coding and merging process was conducted through dedicated focus group sessions among all the authors of this paper. Consequently, any disagreements or ambiguous classification cases were resolved through direct deliberation and consensus-building with the other researchers. A pre-defined rule was established to merge items only if they shared similar functional application scopes within industrial operations, thereby consolidating the raw list of 111 items into 57 distinct skills.

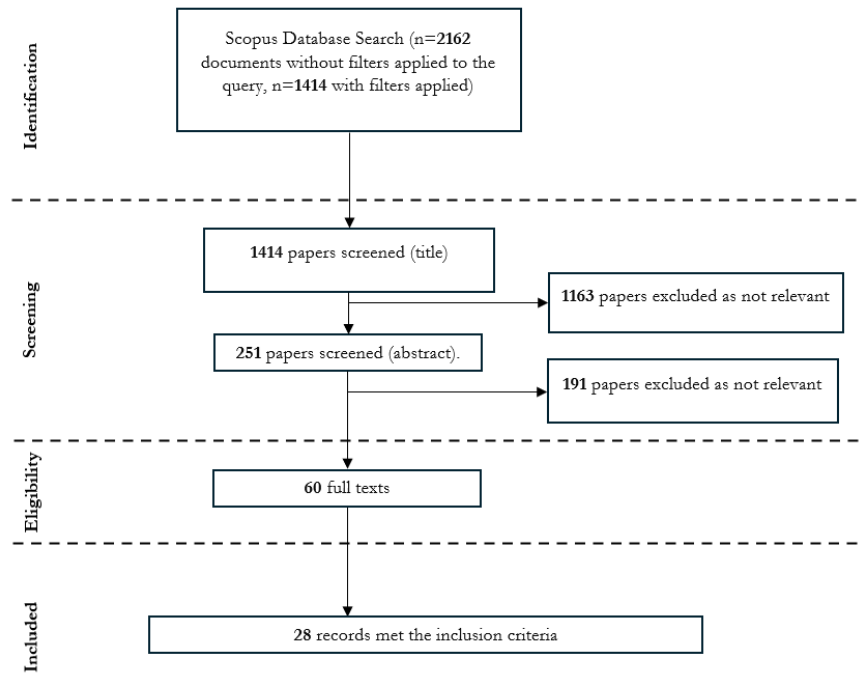


Figure 1. PRISMA flow diagram of the SLR

To enhance analysis clarity, skills were also categorized according to Industry 5.0's four dimensions: resilience-oriented, green-oriented, human-centered, and digital skills. Additionally, a second categorization was used to study the problem from an educational point of view, dividing the skills into 4 categories: methodological, technical, social, and personal. This classification was taken from work done by Hecklau et al. (2016), which presents the categories as follows:

- **Technical (T):** specialized and technical knowledge required for specific job roles, focusing on effective task performance.
- **Methodological (M):** approaches for tackling tasks and solving problems systematically and efficiently.
- **Personal (P):** individual traits affecting how one approaches challenges and achieves goals.
- **Social (S):** skills for effective interpersonal interaction and relationship building.

Once the skills were categorized, a questionnaire was administered to rank them, as previously mentioned.

2.2. Max-Diff Questionnaire

2.2.1. Structure of the Questionnaire

A Max-Diff study was conducted with manufacturing companies to quantitatively assess preferences for skills (Louviere et al., 2015; Marley & Louviere, 2005). Respondents select the best and worst items from multiple sets, enabling comparison across different combinations. This approach creates rankings based on participants identifying the most and least relevant skills in each set. Max-Diff was chosen over Likert scales as it provides clearer skill rankings without flattening differences between items (Magidson et al., 2009).

The questionnaire asked "Which of these skills do you think is the most important and which is the least important?" presenting random sets of skills from the same category. Skills were categorized according to Industry 5.0 dimensions rather than using Hecklau et al.'s (2016) didactic framework (Hecklau et al., 2016), allowing targeted questionnaires for industry experts. Following this logic, four different questionnaires were created: one for resilience-oriented skills, one for green-oriented ones, one for human-centered skills, and one for digital-oriented ones.

Skills sets were randomized for each respondent while ensuring each skill appeared an equal number of times across sets. Survey King, provides an automatic system for creating sets, based on a mathematical formula (1) to derive the ideal number of sets to show to a single respondent in a single questionnaire:

$$\text{Number of times to show each skill} \cdot (\text{total skills} / \text{number of skills per set}) \quad (1)$$

Each set contained six skills, balancing comprehensiveness with evaluation simplicity (Schiano et al., 2020; Sipple et al., 2022), and every skill appeared at least four times to ensure thorough comparison (Orme, 2009). The number of sets created varied by category: 12 for resilience skills, 10 for green skills, and 11 each for human-centered and digital skills. This approach balanced data collection needs against questionnaire length to maintain response quality.

2.2.2. Analysis of the Results

The data collected through Max-Diff questionnaires lends themselves to various types of analysis. In this article, the following were examined: Count Analysis and Share of Preference.

Count Analysis (Orme, 2009) provides a simple analysis specific to the sample, evaluating individual skills with a score based on how often each was chosen as “most relevant” minus times chosen as “least relevant” (2).

$$(\text{Number of times a skill was selected as most relevant} - \text{Number of times a skill was selected as least relevant}) / \text{Number of times the skill was displayed} \quad (2)$$

Positive scores indicate greater preference; negative scores show the opposite. This method ranks skills but is limited to the specific sample without broader population applicability unless the sample is proven representative.

Share of Preference offers more sophisticated analysis through statistical modeling. Using the Multinomial Logit Model, it establishes relative preferences among skills (McFadden, D., 1974; Orme, 2009; So & Kuhfeld, 2007), assigning probabilities to each skill being selected as “most” or “least” relevant. This enables robust modeling of preferences and quantitative insights into skill importance for industrial stakeholders. The Multinomial Logit Model assumes the probability of choosing a category follows a linear function of the alternative’s characteristics and individual preferences (3).

$$P(Y = i|X) = \frac{e^{x_i\beta_i}}{\sum_{k=1}^K e^{x_k\beta_k}} \quad (3)$$

In this formula: Y represents participant choices, X_i describes skills characteristics, β_i shows coefficients for explanatory variables, and K indicates the total number of skills.

Multinomial Logit Model’s key assumption is Independence of Irrelevant Alternatives, meaning the probability ratio between two options remains unaffected by other alternatives. Despite this being difficult to meet in real situations, several measures ensured applicability: varied choice sets, focus on extreme preferences, well-differentiated skills, and balanced skill presentation. In addition to ensuring Independence of Irrelevant Alternatives, the applied Max-Diff is also suitable for the Multinomial Logit model as the mutual exclusivity required by Multinomial Logit Model is satisfied by the selection of only one skill as most or least relevant in the given set. Moreover, the choices are discrete, positioning a skill as either most relevant or least relevant.

Having demonstrated the applicability of the Multinomial Logit model to the Max-Diff study conducted, it is now possible to describe its potential. The Multinomial Logit Model allows probability modeling of skill selection, extending observations beyond the sample. The model was enhanced with Empirical Bayes Regression for more stable preference estimates (Jiang & Zhang, 2010). The resulting utilities enable calculation of odds, preference shares, probabilities, and statistical significance. The share of preference (3) represents the expected fraction of choices for each skill, while odds are calculated as coefficient (of the regression equation) exponentials. Formula (4) determines the probability of a skill being chosen as most relevant.

$$\text{Odds} / (1 + \text{Odds}) \quad (4)$$

This measure and its associated p-value are particularly useful. They provide an easily interpretable output, facilitating decision-makers' understanding of results.

3. Results

3.1. Skills from Literature

From the literature, 111 skills have been extracted, presented in abbreviated form in Table 1. A code has been assigned to each skill, visible in the cell to the left of where the skill is located. Furthermore, references related to each skill are detailed in the table.

Code	Skill	References	Code	Skill	References
S1	3D laser scanning	(Akyazi et al., 2022)	S57	Lifelong learning	(Akyazi et al., 2022; Bueno et al., 2024; Da Silva et al., 2022; Foltynowicz et al., 2024; Guerra & Nørgaard, 2019; Gürdür Broo et al., 2022; Kowal et al., 2022; Kruger & Steyn, 2021; Kulkarni & Patil, 2024; Poláková et al., 2023; Saniuk & Grabowska, 2023, 2024; Suciú et al., 2023; Vogel et al., 2023)
S2	3D printing	(Akyazi et al., 2022)	S58	Machine learning	(Akyazi et al., 2022; Bueno et al., 2024; Gürdür Broo et al., 2022; Salminen et al., 2023; Vogel et al., 2023)
S3	5G network	(Aranda et al., 2023; Saniuk & Grabowska, 2023)	S59	Marketing skills	(Akyazi et al., 2022; Aranda et al., 2023; Taverner et al., 2021)
S4	Using, monitoring and controlling technological devices	(Suciú et al., 2023)	S60	Motivate and commit towards environmental improvement	(Akyazi et al., 2022; Chari et al., 2022; Kulkarni & Patil, 2024; Lagorio & Cimini, 2024)
S5	Work under pressure	(Saniuk & Grabowska, 2023, 2024)	S61	Nanotechnology	(Kolade & Owoseni, 2022)
S6	Acquisition and deployment of Information and Communication technologies	(Akyazi et al., 2022; Kolade & Owoseni, 2022; Saniuk & Grabowska, 2023)	S62	Negotiation	(Akyazi et al., 2022; Bueno et al., 2024; Foltynowicz et al., 2024)
S7	Adaptability to change (= change management)	(Akyazi et al., 2022; Bueno et al., 2024; Chari et al., 2022; Foltynowicz et al., 2024; Knap-Stefaniuk, 2023; Kruger & Steyn, 2021; Kulkarni & Patil, 2024; Vogel et al., 2023)	S63	Network system monitoring	(Kowal et al., 2022)
S8	Aesthetic sensibility	(Taverner et al., 2021)	S64	Networking and integration skills	(Kruger & Steyn, 2021; Lagorio & Cimini, 2024; Saniuk & Grabowska, 2023, 2024)
S9	Agile way of working	(Chari et al., 2022)	S65	Neural networks	(Gürdür Broo et al., 2022)
S10	Analytical skills	(Bueno et al., 2024; Lagorio & Cimini, 2024; Saniuk & Grabowska, 2023, 2024; Suciú et al., 2023)	S66	Opportunity assessment	(Akyazi et al., 2022)

Code	Skill	References	Code	Skill	References
S11	Artificial Intelligence	(Akyazi et al., 2022; Aranda et al., 2023; Bueno et al., 2024; Gürdür Broo et al., 2022; Javaid & Haleem, 2020; Kalateh et al., 2022; Kolade & Owoseni, 2022; Nobre & Tavares, 2023; Salminen et al., 2023; Vogel et al., 2023)	S67	Organisational/managerial skills	(Poláková et al., 2023; Saniuk & Grabowska, 2023)
S12	Attention to human rights, employee well-being and inclusivity	(Chari et al., 2022; Kulkarni & Patil, 2024)	S68	People management	(Akyazi et al., 2022; Bueno et al., 2024; Chari et al., 2022; Foltynowicz et al., 2024)
S13	Augmented reality (AR)	(Akyazi et al., 2022; Aranda et al., 2023; Bueno et al., 2024; Kolade & Owoseni, 2022; Lagorio & Cimini, 2024; Taverner et al., 2021)	S69	Perseverance	(Kruger & Steyn, 2021; Poláková et al., 2023)
S14	Automation	(Bueno et al., 2024; Guerra & Nørgaard, 2019; Krishnamurthy & Harrison, 2023)	S70	Planning and scheduling	(Akyazi et al., 2022; Da Silva et al., 2022)
S15	Autonomy	(Akyazi et al., 2022)	S71	Preventive and predictive maintenance	(Akyazi et al., 2022; Chari et al., 2022; Lagorio & Cimini, 2024)
S16	Business skills	(Akyazi et al., 2022; Kruger & Steyn, 2021; Shet & Pereira, 2021)	S72	Problem solving	(Akyazi et al., 2022; Bueno et al., 2024; Guerra & Nørgaard, 2019; Knap-Stefaniuk, 2023; Lagorio & Cimini, 2024; Poláková et al., 2023; Saniuk & Grabowska, 2023, 2024; Shet & Pereira, 2021; Suciú et al., 2023; Vogel et al., 2023)
S17	Circular business models	(Akyazi et al., 2022; Chari et al., 2022; Nobre & Tavares, 2023)	S73	Process analysis	(Akyazi et al., 2022; Saniuk & Grabowska, 2023, 2024)
S18	Cloud technologies	(Akyazi et al., 2022; Aranda et al., 2023; Bueno et al., 2024; Salminen et al., 2023)	S74	Product management	(Nobre & Tavares, 2023; Taverner et al., 2021)
S19	Collaboration	(Bueno et al., 2024; Chari et al., 2022; Guerra & Nørgaard, 2019; Kalateh et al., 2022; Kulkarni & Patil, 2024; Leon, 2023; Nikitaeva et al., 2024; Onu et al., 2023; Shet & Pereira, 2021; Suciú et al., 2023; Vogel et al., 2023)	S75	Project management	(Bueno et al., 2024; Knap-Stefaniuk, 2023; Taverner et al., 2021)
S20	Communication skills	(Akyazi et al., 2022; Bueno et al., 2024; Da Silva et al., 2022; Foltynowicz et al., 2024; Guerra & Nørgaard, 2019; Kalateh et al., 2022; Knap-Stefaniuk, 2023; Kowal et al., 2022; Kruger & Steyn, 2021; Lagorio & Cimini, 2024; Leon, 2023; Onu et al., 2023; Poláková et al., 2023; Saniuk & Grabowska, 2023, 2024; Suciú et al., 2023; Taverner et al., 2021; Vogel et al., 2023)	S76	Psychological and mental flexibility	(Akyazi et al., 2022)

Code	Skill	References	Code	Skill	References
S21	Competencies in law and policies	(Akyazi et al., 2022; Kruger & Steyn, 2021; Lagorio & Cimini, 2024; Nikitaeva et al., 2024)	S77	Quality management	(Akyazi et al., 2022; Lagorio & Cimini, 2024; Taverner et al., 2021)
S22	Coordination	(Akyazi et al., 2022)	S78	Reliability	(Kowal et al., 2022)
S23	Create suitable financing interests, instruments or structure	(Chari et al., 2022)	S79	Remote control and smart sensing	(Akyazi et al., 2022; Bueno et al., 2024; Lagorio & Cimini, 2024)
S24	Creative thinking	(Bueno et al., 2024; Chari et al., 2022; Guerra & Nørgaard, 2019; Kalateh et al., 2022; Kolade & Owoseni, 2022; Kowal et al., 2022; Krishnamurthy & Harrison, 2023; Kruger & Steyn, 2021; Lagorio & Cimini, 2024; Leon, 2023; Saniuk & Grabowska, 2023, 2024; Suci et al., 2023; Taverner et al., 2021; Vogel et al., 2023)	S80	Renewable energy and advanced energy storage	(Akyazi et al., 2022; Lagorio & Cimini, 2024; Nobre & Tavares, 2023)
S25	Critical thinking	(Akyazi et al., 2022; Bueno et al., 2024; Da Silva et al., 2022; Kalateh et al., 2022; Leon, 2023; Vogel et al., 2023)	S81	Research skills	(Lagorio & Cimini, 2024; Saniuk & Grabowska, 2023, 2024; Shet & Pereira, 2021)
S26	Cross-functional process know-how	(Akyazi et al., 2022)	S82	Rethinking business models that combine physical asset and service as a product	(Bueno et al., 2024; Chari et al., 2022; Nobre & Tavares, 2023)
S27	Cultivate different strategic mindsets	(Chari et al., 2022)	S83	Robotics (also collaborative)	(Akyazi et al., 2022; Aranda et al., 2023; Kolade & Owoseni, 2022; Krishnamurthy & Harrison, 2023; Lagorio & Cimini, 2024; Salminen et al., 2023; Shet & Pereira, 2021; Vogel et al., 2023)
S28	Environmental safety	(Nikitaeva et al., 2024)	S84	Develop and optimize processes and technologies	(Nikitaeva et al., 2024)
S29	Cyber-physical systems	(Akyazi et al., 2022; Bueno et al., 2024; Da Silva et al., 2022; Kowal et al., 2022)	S85	Self-management	(Akyazi et al., 2022)
S30	Cybersecurity	(Akyazi et al., 2022; Aranda et al., 2023; Bueno et al., 2024; Kowal et al., 2022; Salminen et al., 2023; Saniuk & Grabowska, 2023, 2024)	S86	Simulation	(Akyazi et al., 2022; Aranda et al., 2023; Bueno et al., 2024; Chari et al., 2022; Salminen et al., 2023; Shet & Pereira, 2021)

Code	Skill	References	Code	Skill	References
S31	Data management	(Akyazi et al., 2022; Aranda et al., 2023; Bueno et al., 2024; Chari et al., 2022; Gürdür Broo et al., 2022; Javaid & Haleem, 2020; Kowal et al., 2022; Krishnamurthy & Harrison, 2023; Lagorio & Cimini, 2024; Nikitaeva et al., 2024; Shet & Pereira, 2021; Suciú et al., 2023; Vogel et al., 2023)	S87	Social responsibility (ex. Explore social sustainable business models)	(Akyazi et al., 2022; Bueno et al., 2024; Chari et al., 2022; Saniuk & Grabowska, 2023, 2024; Taverner et al., 2021)
S32	Decision making	(Akyazi et al., 2022; Javaid & Haleem, 2020; Kulkarni & Patil, 2024; Nikitaeva et al., 2024; Saniuk & Grabowska, 2023, 2024; Shet & Pereira, 2021)	S88	Social skills	(Foltynowicz et al., 2024; Kalateh et al., 2022)
S33	Design thinking	(Shet & Pereira, 2021)	S89	Strategy skills	(Kruger & Steyn, 2021)
S34	Develop indicators to measure sustainability	(Chari et al., 2022; Kulkarni & Patil, 2024; Nobre & Tavares, 2023)	S90	Supply chain management	(Akyazi et al., 2022)
S35	Develop new manufacturing processes by integrating new technologies	(Chari et al., 2022)	S91	Sustainable product development	(Kulkarni & Patil, 2024; Taverner et al., 2021)
S36	Development of technological and programming solutions	(Suciú et al., 2023)	S92	Sustainable resource management	(Akyazi et al., 2022; Lagorio & Cimini, 2024; Nikitaeva et al., 2024; Taverner et al., 2021)
S37	Digital design (content creation) and optimization	(Bueno et al., 2024; Nobre & Tavares, 2023; Salminen et al., 2023; Shet & Pereira, 2021; Suciú et al., 2023)	S93	Teamworking	(Akyazi et al., 2022; Bueno et al., 2024; Foltynowicz et al., 2024; Kalateh et al., 2022; Kowal et al., 2022; Lagorio & Cimini, 2024; Nikitaeva et al., 2024; Onu et al., 2023; Saniuk & Grabowska, 2023, 2024; Taverner et al., 2021; Vogel et al., 2023)
S38	Digital twin	(Akyazi et al., 2022; Aranda et al., 2023; Lagorio & Cimini, 2024)	S94	Training	(Aranda et al., 2023; Bueno et al., 2024; Chari et al., 2022; Kulkarni & Patil, 2024)
S39	Distributed Ledger Technology and blockchain	(Aranda et al., 2023; Bueno et al., 2024)	S95	Understanding social implications related to the usage of new technologies	(Gürdür Broo et al., 2022)
S40	E-commerce	(Akyazi et al., 2022; Aranda et al., 2023; Nobre & Tavares, 2023; Taverner et al., 2021)	S96	Understanding sustainability main concepts and impacts	(Akyazi et al., 2022; Bueno et al., 2024; Da Silva et al., 2022; Nikitaeva et al., 2024; Nobre & Tavares, 2023)
S41	Electronics	(Akyazi et al., 2022)	S97	Virtual reality	(Akyazi et al., 2022; Aranda et al., 2023; Bueno et al., 2024; Taverner et al., 2021)

Code	Skill	References	Code	Skill	References
S42	Empathy	(Akyazi et al., 2022; Bueno et al., 2024; Foltynowicz et al., 2024; Kalateh et al., 2022)	S98	Visualization	(Bueno et al., 2024; Taverner et al., 2021)
S43	Emotional intelligence	(Bueno et al., 2024; Foltynowicz et al., 2024; Kulkarni & Patil, 2024; Poláková et al., 2023; Suciu et al., 2023)	S99	Be compromising and cooperative	(Foltynowicz et al., 2024; Lagorio & Cimini, 2024; Saniuk & Grabowska, 2023, 2024)
S44	Entrepreneurial thinking and skills	(Akyazi et al., 2022; Kalateh et al., 2022; Lagorio & Cimini, 2024; Saniuk & Grabowska, 2023, 2024; Shet & Pereira, 2021)	S100	Develop effective partnership	(Suciu et al., 2023)
S45	Ethical responsibility	(Akyazi et al., 2022; Bueno et al., 2024; Foltynowicz et al., 2024; Vogel et al., 2023)	S101	Collaborate across all sectors in the supply chain	(Kalateh et al., 2022)
S46	Flexibility	(Bueno et al., 2024; Kulkarni & Patil, 2024; Lagorio & Cimini, 2024; Salminen et al., 2023; Saniuk & Grabowska, 2023, 2024; Shet & Pereira, 2021)	S102	Build trust with stakeholders	(Foltynowicz et al., 2024; Guerra & Nørgaard, 2019)
S47	Health and safety in the workplace	(Akyazi et al., 2022; Vogel et al., 2023)	S103	Using digital technologies to support learning	(Da Silva et al., 2022)
S48	Human-centric design	(Akyazi et al., 2022; Bueno et al., 2024; Da Silva et al., 2022; Lagorio & Cimini, 2024; Salminen et al., 2023)	S104	Risk management	(Knap-Stefaniuk, 2023; Kulkarni & Patil, 2024; Lagorio & Cimini, 2024; Nikitaeva et al., 2024)
S49	Initiative	(Bueno et al., 2024; Poláková et al., 2023; Suciu et al., 2023)	S105	Strategic planning for sustainability	(Kulkarni & Patil, 2024)
S50	Intelligent materials	(Akyazi et al., 2022)	S106	Stress management	(Bueno et al., 2024; Knap-Stefaniuk, 2023)
S51	Intercultural skills (also language)	(Akyazi et al., 2022; Foltynowicz et al., 2024; Knap-Stefaniuk, 2023; Kowal et al., 2022; Onu et al., 2023; Saniuk & Grabowska, 2023, 2024; Vogel et al., 2023)	S107	Additive manufacturing	(Bueno et al., 2024)
S52	Internet of Things	(Akyazi et al., 2022; Aranda et al., 2023; Bueno et al., 2024; Guerra & Nørgaard, 2019; Kolade & Owoseni, 2022; Krishnamurthy & Harrison, 2023; Nobre & Tavares, 2023; Salminen et al., 2023; Shet & Pereira, 2021, 2021)	S108	Coding	(Bueno et al., 2024)
S53	IT systems operation	(Bueno et al., 2024; Knap-Stefaniuk, 2023; Kowal et al., 2022; Lagorio & Cimini, 2024; Nobre & Tavares, 2023)	S109	Think holistically	(Bueno et al., 2024)
S54	Knowledge and experience sharing	(Foltynowicz et al., 2024; Kowal et al., 2022; Lagorio & Cimini, 2024)	S110	Self-confidence	(Bueno et al., 2024)

Code	Skill	References	Code	Skill	References
S55	Leadership	(Akyazi et al., 2022; Bueno et al., 2024; Foltynowicz et al., 2024; Guerra & Nørgaard, 2019; Kalateh et al., 2022; Kulkarni & Patil, 2024; Lagorio & Cimini, 2024; Saniuk & Grabowska, 2023, 2024; Shet & Pereira, 2021; Suciu et al., 2023)	S111	Act professionally according to environmental/ecological principles	(Bueno et al., 2024)
S56	Ensure documentation of reporting in accordance with established sustainability requirements	(Nikitaeva et al., 2024)			

Table 1. Skills from the literature (pre-merging process)

3.2. Skills Merging

Skills in Table 1 were grouped by similarity to create a manageable number for the Max-Diff study. Too many items would have made the survey excessively long, potentially reducing response quality. The grouping process involved evaluating skill descriptions to form meaningful categories, based on the authors' industry experience and research on Industry 4.0/5.0 frameworks. Table 2 shows all grouping steps, with combined skills displayed in the same cell using codes from Table 1. Detailed explanations of groupings are omitted as they would be redundant given the similarities between items. Skills merging reduced the necessary skills for the new industrial context from 111 to 57, which were included in questionnaires for industry experts.

Merging process			
S4 + S35	S30 + S39	S7 + S46	S32 + S72
S3 + S52 + S63	S31 + S98	S24 + S44 + S55	S67 + S70 + S74 + S75
S1 + S2 + S107	S36 + S108	S49 + S66	S27 + S82 + S89
S6 + S53	S38 + S86	S10 + S73	S77 + S104
S11 + S58 + S65	S41 + S79	S15 + S85	S90 + S100 + S101 + S102
S13 + S83 + S97	S50 + S61	S19 + S22	S8 + S20
S14 + S29	S5 + S69 + S76 + S78	S26 + S57	S12 + S68 + S87 + S45
S47 + S106	S48 + S95	S42 + S43	S25 + S33
S9 + S93	S51 + S64 + S88	S62 + S99	

Table 2. Skills merging process in detail

3.3. Categorization of the Skills

Skills extracted from literature were classified into two category systems (see subsection 2.1). Table 3 presents these skills with detailed descriptions, providing clarity on requirements for the new industrial environment. As expected, the digital pillar contains only technical skills related to technology design and implementation, while human-centered and resilience pillars include more methodological, personal, and social skills. Citation counts for each skill are also provided, highlighting which skills receive the most attention in academic literature.

Code	Ability to...	Categorization by Hecklau et al. (2016)	Categorization based on Industry 5.0/Industry 4.0 pillars	Total cits.
SK1	effectively use, monitor, and control and integrate new technologies into manufacturing processes to foster innovation and efficiency	T	D	2
SK2	acquire and strategic deploy Information and Communication Technologies and cloud technologies , ensuring optimal integration for enhanced organizational efficiency	T	D	7
SK3	implement and use Additive Manufacturing and 3D printing , ensuring accuracy and quality in the creation of various objects, and 3D laser scanning technologies to acquire detailed and accurate spatial information for various applications	T	D	2
SK4	increase efficiency by optimizing processes and tasks through the implementation of automated solutions, Collaborative Robotics, and Cyber-Physical Systems	T	D	11
SK5	implement Cybersecurity measures along with Distributed Ledger Technology and Blockchain to secure digital assets and data management, and protect against cyber threats	T	D	6
SK6	organize, analyse, and leverage data , along with creating effective visual representations for informed decision-making	T	D	11
SK7	efficiently create and optimize digital content for maximum impact and engagement	T	D	5
SK8	create virtual models of physical systems for analysis and optimisation (Digital twin and Simulation)	T	D	5
SK9	design, develop and maintain electronics and smart sensing	T	D	1
SK10	use materials with advanced properties for specific applications (intelligent materials)	T	D	2
SK11	connect and optimize devices and systems through the Internet of Things and 5G network enhancing functionality and efficiency and allowing for network systems monitoring	T	D	9
SK12	implement and optimize Neural Networks, Machine Learning and Artificial Intelligence for complex data processing, learning, pattern recognition and predictive modelling	T	D	9
SK13	build immersive digital environments, integrate virtual elements into reality for enhanced experiences like tele-maintenance, using Virtual Reality and Augmented Reality technologies	T	D	4
SK14	use effectively different programming and coding languages	T	D	2
SK15	effectively create and leverage online platforms for business transactions (e-commerce)	T	D	4
SK16	act professionally according to environmental/ecological principles	P	G	1
SK17	design and implement circular business models that minimize waste and promote resource efficiency	T	G	3
SK18	develop and optimize processes and technologies in a sustainable manner	T	G	1

Code	Ability to...	Categorization by Hecklau et al. (2016)	Categorization based on Industry 5.0/Industry 4.0 pillars	Total cits.
SK19	develop indicators to measure sustainability impact	T	G	3
SK20	ensure documentation of reporting in accordance with established sustainability requirements	T	G	1
SK21	ensure environmental safety of processes in case of failure	T	G	1
SK22	motivate and commit to environmental improvement , showing dedication to sustainable practices and initiatives	P	G	3
SK23	use renewable energy and design advanced energy storage , demonstrating the ability to leverage and manage sustainable energy solutions	T	G	2
SK24	engage in strategic planning for sustainability , managing actions to ensure long-term positive impacts on the environment	M	G	1
SK25	create environmentally conscious products through eco-friendly practices and material (sustainable product development)	T	G	2
SK26	optimize resource usage to minimize environmental impact (sustainable resource management)	T	G	2
SK27	integrate sustainable practices into decision-making processes	M	G	3
SK28	promote and foster inclusivity , lead, motivate, and supervise teams for enhanced productivity and collaborative success (people management), and explore and implement socially sustainable business models (social responsibility)	S	HC	7
SK29	be compromising and cooperative, demonstrating skills in reaching mutually beneficial agreements and resolving conflicts (negotiation)	S	HC	3
SK30	collaborate with various people and teams to achieve shared goals, along with the capacity to effectively manage and synchronize tasks, resources, and activities for optimized process execution (coordination)	S	HC	12
SK31	communicate clearly and concisely for effective collaboration with various stakeholders	S	HC	14
SK32	analyse and evaluate information for decision-making (critical thinking) and understand user needs for innovative solutions (design thinking)	M	HC	6
SK33	empathize with others , understand, and effectively manage emotions in themselves and others	P	HC	5
SK34	create and manage a safe and healthy work environment	M	HC	2
SK35	design products and systems that prioritise user experience and meet human needs (human-centred design), coupled with an understanding of the social implications associated with the use of new technologies	M	HC	4
SK36	collaborate and disseminate information effectively within a team or organization (knowledge and experience sharing)	S	HC	1
SK37	demonstrate and act with self-confidence	P	HC	1

Code	Ability to...	Categorization by Hecklau et al. (2016)	Categorization based on Industry 5.0/Industry 4.0 pillars	Total cits.
SK38	communicate and collaborate effectively across diverse cultural backgrounds (intercultural skills) and access outsourced expertise and knowledge (social, networking and integration skills)	S	HC	8
SK39	handle stressful situations effectively	P	HC	1
SK40	effectively collaborate within teams (teamworking) and apply Agile principles to work methods	S	HC	8
SK41	think holistically , globally and act locally	P	HC	1
SK42	transmit knowledge and skills effectively, contributing to individual and group development (training)	S	HC	3
SK43	work under pressure , maintain mental flexibility in navigating dynamic and challenging situations, and consistently show perseverance and reliability	P	R	7
SK44	make independent decisions and effectively manage tasks without constant supervision (self-management)	P	R	1
SK45	develop optimal financing strategies, instruments or structures , showcasing the ability to create specific financial solutions that align with organisational goals and resilience objectives	M	R	1
SK46	understand and adhere to legal and regulatory frameworks , with a deep understanding of policies relevant to the industry, ensuring compliance and mitigating legal risks	T	R	4
SK47	identify and seize opportunities through a proactive and innovative approach (creative and entrepreneurial thinking), and guide, inspire, and influence individuals and teams toward achieving common goals (leadership skills)	M	R	17
SK48	develop effective partnerships , collaborate across all sectors in the supply chain , manage the supply chain , and build trust with stakeholders	M	R	5
SK49	adapt to changing circumstances and navigate ambiguity with agility (change management and flexibility)	M	R	13
SK50	identify and address problems and assess opportunities (initiative)	M	R	4
SK51	coordinate and optimise processes between the different functional areas of an organisation (cross-functional process know-how) and commit to lifelong learning	M	R	12
SK52	effectively plan, coordinate, and manage tasks and processes in an organizational setting, while considering resilience in the face of potential sudden changes (organizational and managerial skills)	M	R	7
SK53	analyse complex issues and implement effective solutions (problem solving) and make effective and timely decisions based on a considered assessment of available information (decision making)	M	R	13
SK54	collect, understand, and analyse information for informed decision-making and problem-solving (analytical skills), as well as for assessing and optimizing process efficiency and productivity (process analysis)	M	R	6

Code	Ability to...	Categorization by Hecklau et al. (2016)	Categorization based on Industry 5.0/Industry 4.0 pillars	Total cits.
SK55	ensure that products or services meet established standards and manage risks, including the identification, assessment and mitigation of potential threats to organisational objectives (quality and risk management)	M	R	6
SK56	conduct comprehensive research by formulating research questions with a long-term vision, employing different methodologies and synthesizing the findings (research skills)	M	R	4
SK57	recognize when to abandon failing or outdated areas or methods (strategy skills) and develop different strategic mindsets	M	R	4

Hecklau Categorization: Technical (T), Social (S), Methodological (M), Personal (P)

Industry 5.0 Categorization: Digital (D), Green (G), Human-Centricity (HC), Resilience (R)

Table 3. Categorization of the skills

4. Discussion

4.1. Max-Diff Analysis

As discussed in Subsection 2.2, MaxDiff surveys were distributed to industry experts specialized in Industry 5.0 pillars: resilience (10 experts), human-centricity (13), sustainability (10), and digitalization (12). Experts were strategically selected from manufacturing companies of varying sizes in Northern Italy, including roles such as Chief Executive Officers, Chief Operating Officers, Innovation Managers, and Human Resource Managers. Company sizes were well-distributed: 19% had <50 employees, 31% had 51-250, 16% had 251-499, and 34% had >500. Regarding work experience of the respondents, 19% had 1-9 years, 31% had 10-19 years, 25% had 20-29 years, and 25% had 30+ years.

Despite the limited sample size, the survey produced clear consensus on the most and least relevant skills, as validated by the significant *p-values* (< 5%) presented in the following tables. The results of the Max-Diff analysis are reported below for each of the skill categories related to Industry 5.0, according to the adopted categorization. For each category, the values of Share of Preference (the fraction of choices in which skill *i* was indicated as the most relevant), the Probability that the skill is chosen as the most or least relevant, the associated *p-value*, and the Count Analysis are presented.

4.1.1. Digital Skills

Table 4 shows the digital skills with their respective parameters. The most relevant skill proved to be the ability to organize, analyze, and leverage data (SK6). This strong preference is robustly supported by its primary statistical indicators, achieving the highest Share of Preference (14.86%) and a high probability of being chosen as the most relevant item (72.24%, *p-value* < 0.01%), which aligns consistently with a high positive Count Analysis score of 0.45. Closely following this lead, the next most highly prioritized digital competencies are SK1 (using and integrating new technologies in existing processes) and SK11 (using and integrating Internet of Things systems and 5G networks for process monitoring). Both skills yielded highly significant statistical relevance (below 5%), indicating a shared perception of importance. Conversely, the competencies that received the lowest scores in terms of Share of Preference, probability, and Count Analysis are: SK14 (using different programming languages), SK10 (using smart materials), SK3 (using 3D printing technologies and 3D laser scanning) and SK15 (implementing online e-commerce platforms). These specific indicators reflect a lower perceived priority and a shared consensus among the industry experts regarding their limited immediate relevance.

The findings highlight a clear trend toward the growing importance of the data-centric and technology-driven skills in the smart manufacturing domain. In particular, data-informed decision-making, technology integration

and real-time data sharing are confirmed as crucial factors for remaining competitive in the market with an increasing need for companies to equip themselves with these technical skills as key drivers of performance and innovation.

Skill Code	Categorization by Hecklau et al. (2016)	SP	Probability	p-Value	CA
SK6	T	14,86%	72,24%	0,00%***	0,45
SK1	T	11,05%	65,93%	0,17%***	0,32
SK11	T	10,42%	64,60%	0,19%***	0,29
SK8	T	8,20%	58,96%	7,40%*	0,18
SK4	T	7,89%	58,01%	9,10%*	0,16
SK12	T	7,33%	56,22%	22,20%	0,13
SK2	T	6,77%	54,24%	41,09%	0,09
SK9	T	6,25%	52,26%	67,07%	0,05
SK5	T	6,12%	51,75%	70,85%	0,04
SK7	T	5,32%	48,25%	70,85%	-0,04
SK13	T	5,19%	47,63%	66,34%	-0,05
SK15	T	3,89%	40,55%	4,27%**	-0,19
SK3	T	2,90%	33,68%	0,05%***	-0,33
SK10	T	2,01%	26,06%	0,00%***	-0,48
SK14	T	1,79%	23,82%	0,00%***	-0,53

*** < 1%; ** < 5%; * < 10%

Table 4. Share of preference (SP), probability of choice as most relevant, p-value and Count Analysis (CA) for digital skills

4.1.2. Green Skills

As can be noted in Table 5, the green skills most valued by the analyzed sample are those related to sustainability strategies and process innovation, namely SK24 (the ability to strategically plan for sustainability), with a Share of Preference of 16.00%, a probability of choice of 68.29%, and a positive Count Analysis of 0.37, followed by SK18 (developing and optimizing processes with a sustainable perspective) and SK17 (designing and implementing circular business models). On the contrary, the more operational or support skills, such as SK22 (motivating environmental improvement) and SK20 (ensuring documentation reporting with the requirements established by regulations) show significantly lower Share of Preference values (4.65% and 3.78% respectively) and present a negative Count Analysis (-0.23 and -0.33), indicating that these skills were more often chosen as less relevant or are otherwise less appreciated by respondents. This suggests a strong emphasis on strategic and systemic approaches to sustainability, with attention ranging from strategic long-term planning for sustainability with a focus on circularity practices to operational improvements to reduce environmental impact while maintaining efficiency. These results suggest that sustainability is not just a matter of compliance to regulation but it is considered strategic for innovation and competitiveness, with methodological and technical skills sought by companies and preferred to the personal ones.

Skill Code	Categorization by Hecklau et al. (2016)	SP	Probability	p-Value	CA
SK24	M	16,00%	68,29%	0,04%***	0,37
SK18	T	15,06%	66,96%	0,18%***	0,34
SK17	T	12,51%	62,73%	1,93%***	0,26
SK19	T	8,61%	53,69%	44,27%	0,07
SK26	T	8,32%	52,82%	56,10%	0,06
SK27	M	7,12%	48,94%	83,69%	-0,02
SK21	T	6,95%	48,34%	71,55%	-0,03
SK25	T	5,97%	44,57%	25,44%	-0,11
SK23	T	5,82%	43,90%	22,76%	-0,12
SK16	P	5,20%	41,15%	9,42%*	-0,18
SK22	P	4,65%	38,51%	1,99%***	-0,23
SK20	T	3,78%	33,74%	0,15%***	-0,33

*** < 1%; ** < 5%; * < 10%

Table 5. Share of preference (SP), probability of choice as most relevant, p-value and Count Analysis (CA) for green skills

4.1.3. Human-Centred Skills

Table 6 reports the results for the human-centered skills category. Among these, SK30 (collaborating with various people for achieving shared objectives and ability to manage resources and activities effectively) stands out as the most relevant skill, with a Share of Preference of 12.57%, a probability of being chosen as most relevant of 67.59%, a highly significant *p-value* of 0.01%, and a Count Analysis score of 0.35. Similarly, SK36 (sharing knowledge and experience) and SK32 (critical and design thinking) follow closely, both showing strong statistical significance and positive Count Analysis values (0.33 and 0.24 respectively), highlighting their critical role in the human-centered dimension. Conversely, several skills including SK39 (stress management) and SK37 (self-confidence) exhibit low Share of Preference (2.71% and 1.80%), low probabilities, and notably negative Count Analysis values (-0.38 and -0.54), reflecting a general perception of these abilities as less relevant within the sample.

This result shows that the competences perceived as fundamental for success in the Industry 5.0 context are the social ones, emphasizing the importance of collaborative and structured thinking skills, while the abilities more focused on personal management, such as stress management and self-confidence, are considered less priority by respondents. The results show the need for companies to have people who can not only work in an interdisciplinary environment by coordinating efforts toward common goals, but also foster a culture of openness and continuous learning, which is considered essential for innovation. Moreover, in the era of AI, the development of critical thinking is becoming increasingly crucial to succeed in a complex and dynamic work environment.

Skill Code	Categorization by Hecklau et al. (2016)	SP	Probability	p-Value	CA
SK30	S	12,57%	67,59%	0,01%***	0,35
SK36	S	12,02%	66,61%	0,05%***	0,33
SK32	M	9,78%	61,87%	0,82%***	0,24
SK35	M	8,58%	58,74%	6,29%*	0,18
SK34	M	8,31%	57,97%	11,19%	0,16
SK42	S	6,68%	52,56%	57,83%	0,05
SK28	S	6,24%	50,86%	85,30%	0,02

Skill Code	Categorization by Hecklau et al. (2016)	SP	Probability	p-Value	CA
SK33	P	6,03%	50,00%	100,00%	0
SK31	S	5,59%	48,12%	69,83%	-0,04
SK38	S	5,46%	47,51%	58,47%	-0,05
SK40	S	5,09%	45,78%	35,87%	-0,08
SK29	S	4,97%	45,21%	32,85%	-0,1
SK41	P	4,16%	40,86%	7,12%*	-0,18
SK39	P	2,71%	31,02%	0,00%***	-0,38
SK37	P	1,80%	22,96%	0,00%***	-0,54

*** < 1%; ** < 5%; * < 10%

Table 6. Share of preference (SP), probability of choice as most relevant, p-value and Count Analysis (CA) for human-centred skills

4.1.4. Resilience-Oriented Skills

Table 7 presents the results for the resilience skills category. Among these, SK54 (collecting and analyzing information to make informed decisions) emerges as the most relevant skill, with a Share of Preference of 14.03%, a probability of being chosen as most relevant of 70.60%, a highly significant p-value of 0.01%, and a Count Analysis score of 0.41. Close behind are SK49 (flexibility and change management) and SK53 (problem solving), both showing strong statistical significance and positive Count Analysis values (0.35 and 0.27 respectively), emphasizing their crucial role in building resilience within the Industry 5.0 framework. Conversely, skills such as SK44 (making decisions independently) and SK56 (conducting in-depth research with a long-term vision) exhibit low Share of Preference values (2.44% and 3.01%), low probabilities, and notably negative Count Analysis scores (-0.42 and -0.32), indicating they are perceived as less relevant by respondents. Additionally, SK45 (developing optimal financing strategies) and SK50 (identifying problems and opportunities) received low ratings, suggesting lower relevance among the surveyed population.

The most valued resilience skills appear to be those that facilitate proactivity and dynamic management of complex and rapidly changing situations, while skills more focused on long-term decision making or strategic aspects appear less urgent or less shared in the specific survey context. This result highlights the strong demand for people, on the one hand, with evidence-based thinking and the ability to make data-driven decisions (strongly consistent with the findings in the digital and human-centered pillars) and, on the other hand, with adaptive and problem-solving skills.

Skill Code	Categorization by Hecklau et al. (2016)	SP	Probability	P-Value	CA
SK54	M	14,03%	70,60%	0,01%***	0,41
SK49	M	12,09%	67,31%	0,11%***	0,35
SK53	M	10,17%	63,41%	0,68%***	0,27
SK48	M	6,46%	59,05%	9,08%*	0,18
SK51	M	7,99%	57,65%	17,71%	0,15
SK52	M	7,82%	57,11%	15,96%	0,14
SK57	M	6,11%	51,09%	84,18%	0,02
SK47	M	5,87%	50,00%	100,00%	0
SK43	P	5,39%	47,88%	68,07%	-0,04
SK55	M	5,36%	47,74%	67,07%	-0,05
SK46	T	4,41%	42,89%	15,96%	-0,14

Skill Code	Categorization by Hecklau et al. (2016)	SP	Probability	P-Value	CA
SK50	M	3,62%	38,13%	0,82%***	-0,24
SK45	M	3,23%	35,48%	0,50%***	-0,29
SK56	M	3,01%	33,92%	0,90%***	-0,32
SK44	P	2,44%	29,33%	0,00%***	-0,42

*** < 1%; ** < 5%; * < 10%

Table 7. Share of preference (SP), probability of choice as most relevant, p-value and Count Analysis (CA) for resilience-oriented skills

4.2. Competence Network Analysis

A network analysis based on scientific literature was conducted to examine skill interrelationships. This analysis, depicted in Figure 2, aims to visually represent both the frequency of skills mentioned in scientific literature and their conceptual relationships; specifically, how often they appear together in academic works. These results were discussed also considering the MaxDiff study. The comparison between MaxDiff data and the literature-based network offers interesting points for reflection since it is important to emphasize that a high number of citations in literature does not necessarily imply a greater intrinsic importance of the skill, but rather a greater interest from the scientific community.

The networks were created using Python with NetworkX (NetworkX, 2025) and Matplotlib (Droettboom, 2025) libraries. Each node represents a skill, with edges indicating skills cited together in articles. Edge thickness shows connection strength (number of co-occurrences), while node size reflects the skill's mention frequency in analyzed papers. To improve readability, only connections with weight ≥ 3 (skills co-cited at least three times) were included, highlighting significant relationships while reducing noise. Finally, node colors indicate skill categories: orange (resilience), pink (human-centered), blue (digital), and green (green skills). Edges between skills in the same category match their node color, while inter-categorical connections appear in red.

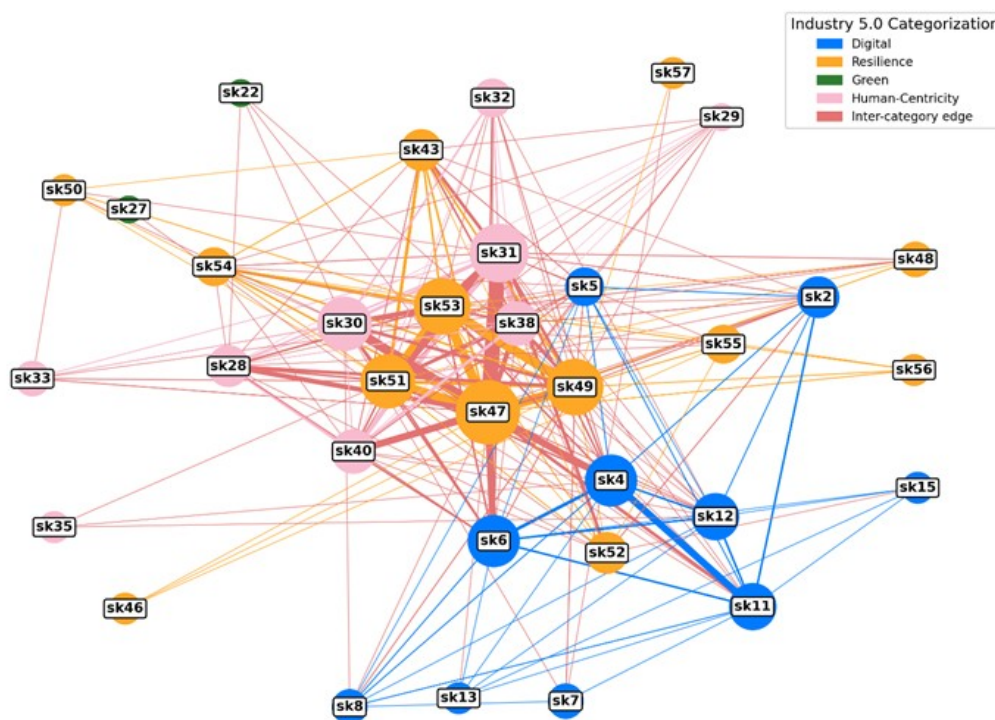


Figure 2. Network of skills categorized by Industry 5.0 Pillars

The network analysis based on the classification of Industry 5.0 pillars (Figure 2) reveals a central core of skills widely cited in scientific literature, visually represented by larger nodes and a high density of connections. The ten most recurring skills include four digital skills (SK4, SK6, SK11, SK12), four resilience-oriented skills (SK47, SK49, SK51, SK53), and two human-centered ones (SK30 and SK31). These skills are not only frequently mentioned in scientific contributions, but also occupy central positions within the network, suggesting a close interdependence among them. This indicates that literature tends to treat them in an integrated manner, showing the emergence of professional profiles that require a synergistic combination of digital, resilient, and human-centered skills.

The position of resilient skills within the graph is particularly relevant. SK47 (creative and entrepreneurial thinking, leadership skills), SK49 (change management and flexibility), SK53 (problem solving and decision making), and SK51 (cross-functional process know-how, lifelong learning) are among the largest and most interconnected nodes, confirming how the ability to face complexity, manage continuous changing situations, and maintain operational continuity in uncertain scenarios represents a key theme in the current industrial transformation. These results are consistent also with the results of Max-Diff study, where SK49 and SK53 were considered priorities also from practical point of view, further emphasizing the need for a workforce characterized by flexibility, proactivity and ability to work in interdisciplinary teams, not only in terms of technical competences but also from a social point of view. In particular, SK53 (problem solving and decision making) is the only skill that is simultaneously among the most cited, most connected, and most relevant per MaxDiff - suggesting it may be viewed as a foundational competence for orchestrating the application of all others.

Digital skills also stand out for their density and centrality, with SK6 (data analysis and visualization), SK4 (collaborative robotics) and SK12 (AI, ML) showing robust links with resilient and human-centered skills, highlighting how technological innovation is now inextricably linked to leadership and decision-making capacity. SK6, in particular, emerges as a “bridge skill”, frequently co-cited with SK53 and SK31, indicating that data literacy is seen not only as a technical competence but also as a facilitator of better decision-making and more clear communication among stakeholders. Similarly, SK11 (Internet of Things) is closely tied to leadership (SK47), confirming that technologies aren’t viewed as stand-alone assets, but are deeply connected with organizational transformation and require strategic guidance for their implementation and exploitation. SK6 and SK11 received high priority also in the Max-Diff study, demonstrating how the ability to extract valuable information from data coming from different sourcing and integrating manufacturers and consumers is nowadays one of the main skills required in the job market.

The human-centered skills SK30 (collaboration and teamwork) and SK31 (clear communication) also occupy central positions, highlighting the increasing relevance of socio-relational capabilities in digitally and operationally complex environments. Their proximity to both digital and resilience-oriented skills suggest a growing recognition that technical and strategic effectiveness cannot be separated from the human dynamics that underpin coordination and trust-building. The tight link between SK31 (clear communication) and SK47 (leadership), for instance, suggests a model of change management that integrates creative thinking and leadership capabilities. Collaboration and teamwork are perceived relevant also from the practitioner perspective, again emphasizing the high level of integration and interconnection required in the work environment as a mean to foster innovation. An interesting exception is SK36 (knowledge and experience sharing), which was identified as a high-relevance skill in the MaxDiff study but is absent from the graph because it doesn’t reach the minimum threshold of three co-citations. This suggests that scientific literature may give per granted this competency compared to its perceived utility in operational contexts, because knowledge sharing is one of the missions of researchers. Conversely, some skills such as SK56 (research skills) appear in the graph but received low scores in the MaxDiff study, underlining the existing gap between academia and practice.

While technical and engineering skills remain highly valued, these findings suggest incorporating activities in technical education (such as engineering programs) that develop essential soft skills including flexibility, change management, problem solving, critical thinking, leadership, communication, and teamwork across disciplines. This can be accomplished through courses based on real or simulated real-world problems, challenge and problem based learning, interdisciplinary collaborative projects, and design thinking workshops (Doulougeri et al., 2024; Henderson et al., 2025; Kosmodemyanskaya et al., 2019). Providing students with realistic contexts can also be

achieved through teaching and learning factories, which offer environments where students can experiment with various solutions to real problems while observing the effects of their decisions on the system (Lagorio & Cimini, 2024; Pittich et al., 2020). This trial-and-error approach, supported by an ideal implementation environment, aligns well with Kolb's learning cycle, which is recognized as an effective educational model for developing and strengthening skills in learners of specific activities (Kolb, 1984).

This learning approach should extend beyond young scholars to include practitioners as part of lifelong learning, a crucial component in today's complex and dynamic industrial environments (Diaz Lantada, 2020).

Analyzing the network graph, it is worth noticing the absence of green skills among the central skills of the network: none of them appear among the top ten nodes by size, and many do not even meet the graphical representation constraint. The only two green skills that appear in the network are SK22 (motivation and commitment to environmental improvement) and SK27 (integration of sustainability into decision-making processes), but both appear in peripheral positions and are poorly connected. This thematic isolation may indicate a segmentation in academic contributions: although sustainability is widely recognized as a key dimension of Industry 5.0, it is still treated as a specialized sector, not always integrated into broader models of industrial innovation. The disconnection of green skills appears even more evident in this cross-comparison: the green skills considered the most important in the MaxDiff study (strategic planning for sustainability - SK24, optimization of processes in a sustainable way - SK18, and the design of circular business models - SK17) are not even represented in the graph. This means that, in scientific literature, green skills are not only less cited in absolute terms, but tend to be discussed as separate domains, without strong integration with digital, human-centered, or resilience-oriented skills. Green skills seem to be acknowledged as necessary, but not yet fully “translated” into integrated competency frameworks. The fact that they do not emerge as central in the graph, nor as interconnected hubs, signals the lack of a consolidated view that places them as transversal elements to other skills. Sustainability thus appears as an “added” thematic dimension, treated vertically or thematically separated, rather than as a transversal directive, integrated into digital innovation processes, human-centered or resilient organizational transformation. This result shows the relevance of better incorporating also sustainability dimensions in the educational program, not only from technical point of view but also as a mean to create professionals with a mindset oriented to sustainability and ensure that this would be a solid long-lasting objective for future generations.

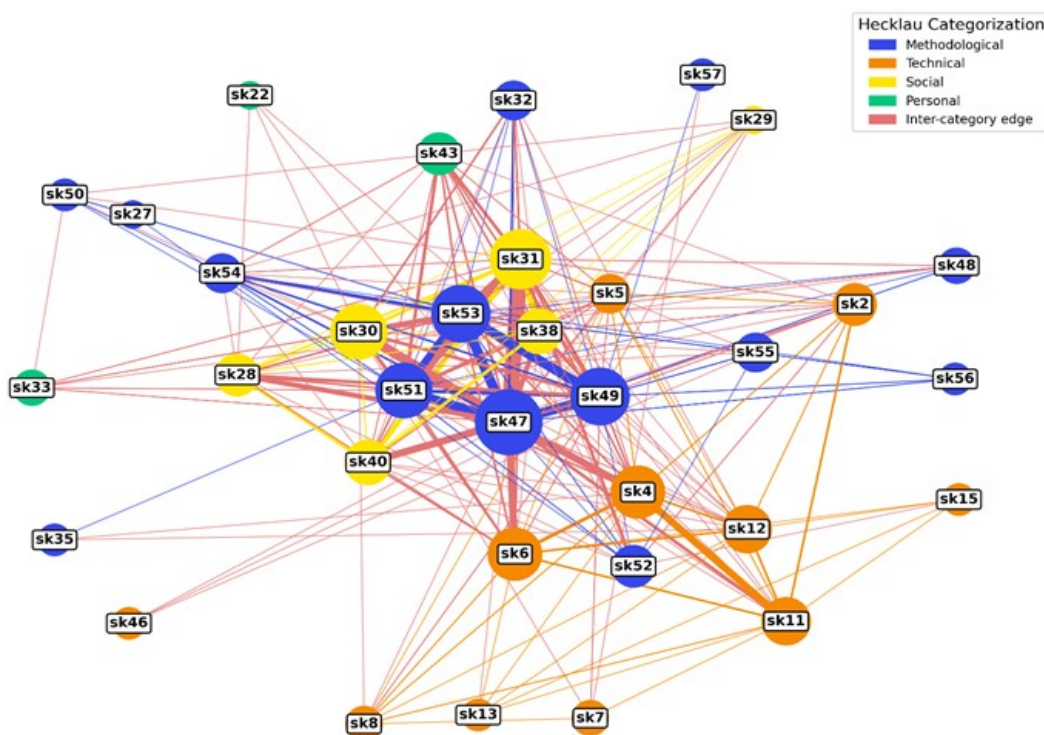


Figure 3. Network of skills categorized according to Hecklau (Hecklau et al., 2016)

A further analysis has been carried out according to Hecklau's classification. As before, the coloring of nodes varies based on the skill's category: methodological skills are represented in blue, technical ones in orange, social in yellow, and personal skills in green. The edges also follow the chromatic logic explained before. This network analysis reveals an articulated map with a clear central core of interconnected methodological, technical, and social skills. The network highlights four central methodological skills, SK47 (creative and entrepreneurial thinking, leadership skills), SK49 (change management and flexibility), SK53 (problem solving and decision making), and SK51 (cross-functional process know-how, lifelong learning), which form a transversal cluster in the graph. These represent enabling skills that connect different domains and support integration between technological, organizational, and human dimensions. The methodological skills SK47 and SK49 are also strongly correlated with social skills such as SK31 (clear communication), indicating that in advanced industrial contexts, change management and leadership are increasingly linked to relational and soft dimensions, such as the ability to effectively communicate objectives and strategies.

Technical skills (SK4, SK6, SK11, and SK12) show numerous connections, especially with methodological skills. This configuration highlights that mastering digital tools, data analysis, and emerging technologies is not enough without the capacity for strategic application, problem-solving, and continuous learning. The relationship between SK6 (data analysis and visualization) and SK47 is significant, showing how modern leadership must be based on the ability to interpret data and transform it into operational insights. Today's leader not only guides with vision but also knows how to interpret informational complexity and make evidence-based decisions. SK4 (automation and robotics) also presents strong links with methodological and social skills, demonstrating that the adoption of advanced technologies requires both technical knowledge and awareness of their organizational and human impacts. Robotization transforms roles, processes, and human interactions, explaining why in papers it is often associated with themes such as leadership, continuous learning, communication, and coordination.

The social skills among the central nodes - SK30 (collaboration and coordination), SK31, SK38 (intercultural understanding), and SK40 (teamwork) - play a crucial role in the network, directly interfacing with methodological skills. This structure underlines how effective collaboration, intercultural understanding, and teamwork are necessary conditions for implementing complex technologies and methodologies. In particular, the connections between SK30 and SK53 (problem solving and decision making), and between SK30 and SK47, suggest that the ability to solve problems requires a solid communicative and collaborative context. In increasingly interconnected and multicultural production environments, communication becomes a strategic factor that influences the effectiveness of decisions and organizational adaptation. The network ultimately indicates a systemic rather than fragmented competency model, where technical, methodological, and social skills are interdependent and converge toward hybrid professional profiles that integrate technology and the human dimension. This reflects an evolved vision of Industry 4.0 requirements, where technical specialization is accompanied by solid capacities for learning, adaptation, and human interaction.

5. Conclusion

This study explored and prioritized key skills associated with the transition toward Industry 5.0. Through systematic literature review and MaxDiff analysis with manufacturing experts, the perceived relevance and interrelationships between critical skills were identified and examined. The findings reveal that beyond technical and digital skills, this evolving industrial paradigm tends to demand methodological, social, and human-centered skills, highlighting the need for hybrid professionals who can integrate technology, sustainability, resilience and human values.

This study provided a structured overview of the most relevant skills discussed under the scope of Industry 5.0 and offered valuable insights into their importance and relationships. However, several limitations should be acknowledged. The MaxDiff survey, for example, has inherent limitations despite being conducted with industry experts. The sample was relatively small and primarily focused on manufacturing. Consequently, the findings may not fully apply to other sectors like healthcare or agri-food, or to non-European industrial contexts where the concept of Industry 5.0 is often argued to develop differently. Furthermore, respondents evaluated skills that were already grouped based on the literature review, potentially influencing their assessment or limiting their ability to introduce emerging skills. Additionally, this study's scope was limited to identifying and prioritizing skills, without

exploring how they should be developed or assessed within educational systems. Finally, regarding the gender perspective, this study focuses on skills required at a general industrial level; therefore, a sex-based differentiation was not applicable to the research objectives and has not been analysed.

Building upon these identified limitations, future research should establish a deeper pedagogical investigation to understand how these skills can be developed synergistically. Furthermore, future research should explore effective ways to develop these skills through tailored teaching strategies and practical training models, particularly in higher education and lifelong learning programs. Validating and refining the skillset would benefit from studies of sector-specific needs and cross-industry comparisons. Research could also assess how these skills affect organizational performance and worker well-being, helping align educational initiatives with measurable industry outcomes. Finally, future research could replicate the MaxDiff analysis from an educational perspective, using the Hecklau classification as a foundation. This approach might identify differences in how skills are prioritized and related when viewed from pedagogical rather than industrial perspectives. Comparing results from educational and industry experts could reveal meaningful divergences and help align curriculum design with both market demands and learning objectives.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

This paper was supported by National Recovery and Resilience Plan (NRRP), Mission 4 Component 2 Investment 1.1 – Call for tender No. 1409 of 14/09/2022 of Italian Ministry of University and Research funded by the European Union (NextGenerationEU), Project “TechFact - Design and adoption of Teaching Factories, Learning Spaces and Learning Activities for fostering the education of a responsible generation of engineers and technical students” (Nr. P202239XAE, CUP F53D23009290001).

Authors' contributions

Luca Carminati: Conceptualisation, Methodology, Data Curation, Formal Analysis, Writing – Original Draft, Writing – Review & Editing.

Roberto Sala: Conceptualisation, Methodology, Writing – Review & Editing, Formal Analysis.

Fabiana Pirola: Conceptualisation, Methodology, Funding Acquisition, Writing – Review & Editing, Formal Analysis.

Rossella Pozzi: Conceptualisation, Methodology, Writing – Review & Editing.

Mohammad Hossein Dehbozorgi: Conceptualisation, Writing – Review & Editing.

Monica Rossi: Conceptualisation, Methodology, Writing – Review & Editing.

Data availability

Data included in the article itself or supplementary material.

Use of Artificial Intelligence

The authors used DeepL Write and Google Gemini to refine the wording and fluency of the text and take full responsibility for the content of the publication.

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Appendix

To ensure the transparency and reproducibility of the empirical findings presented in this study, this appendix provides the complete input data structures and Python code utilized for the network analysis. Appendix A outlines the direct association between each selected bibliographic source and the operationalized skill codes. Appendix B presents the taxonomic classification mappings under both the Hecklau framework (Typology H) and the Industry 5.0 framework (Typology I). Finally, the complete Python code used to construct the network edge-weights, calculate node sizes based on literature frequencies, and generate the visualizations is provided in Appendix C.

A. Paper & Skill list (Python input file)

Paper	Year	Skill_List
Kruger & Steyn 2021	2021	SK43;SK31;SK46;SK47;SK49;SK51;SK38;SK57
Kowal et al. 2022	2022	SK43;SK2;SK4;SK31;SK47;SK5;SK6;SK11;SK36;SK51;SK38;SK40
Aranda et al. 2023	2023	SK4;SK5;SK6;SK8;SK11;SK12;SK42;SK13;SK15
Suciu et al. 2023	2023	SK30;SK31;SK47;SK6;SK48;SK33;SK50;SK51;SK53;SK54;SK14
Javaid & Haleem 2020	2020	SK6;SK12;SK53
Taverner et al. 2021	2021	SK28;SK31;SK47;SK6;SK52;SK55;SK25;SK26;SK40;SK13;SK15
Chari et al. 2022	2022	SK28;SK45;SK17;SK30;SK47;SK6;SK19;SK7;SK8;SK49;SK22;SK57;SK40;SK42
Leon 2023	2023	SK30;SK31;SK47;SK32
Kolade & Owoseni 2022	2022	SK2;SK4;SK47;SK10;SK11;SK12;SK13
Da Silva et al. 2022	2022	SK4;SK31;SK32;SK35;SK51;SK52;SK27
Akyazi et al. 2022	2022	SK43;SK2;SK3;SK28;SK4;SK44;SK29;SK17;SK30;SK31;SK46;SK47;SK32;SK5;SK6; SK48;SK8;SK9;SK33;SK49;SK34;SK35;SK50;SK10;SK11;SK51;SK22;SK12;SK52;SK53; SK54;SK55;SK23;SK38;SK26;SK40;SK27;SK13;SK15
Saniuk & Grabowska 2023	2023	SK43;SK2;SK28;SK29;SK31;SK47;SK5;SK49;SK51;SK52;SK53;SK54;SK56;SK38;SK40
Shet & Pereira 2021	2021	SK4;SK30;SK47;SK32;SK6;SK7;SK8;SK49;SK11;SK53;SK56
Gürdür Broo et al. 2022	2022	SK6;SK35;SK51;SK12
Saniuk & Grabowska 2024	2024	SK43;SK28;SK29;SK31;SK47;SK5;SK49;SK51;SK53;SK54;SK56;SK38;SK40
Poláková et al. 2023	2023	SK43;SK31;SK33;SK50;SK51;SK52;SK53
Salminen et al. 2023	2023	SK2;SK4;SK5;SK7;SK8;SK49;SK35;SK11;SK12
Guerra & Nørgaard 2019	2020	SK4;SK30;SK31;SK47;SK48;SK11;SK51;SK53
Kalateh et al. 2022	2022	SK30;SK31;SK47;SK32;SK48;SK33;SK12;SK38;SK40
Nobre & Tavares 2023	2023	SK2;SK17;SK19;SK7;SK11;SK12;SK52;SK23;SK57;SK27;SK15
Kulkarni & Patil 2024	2024	SK28;SK30;SK47;SK19;SK33;SK49;SK51;SK22;SK53;SK55;SK24;SK25;SK42
Knap-Stefaniuk 2023	2023	SK2;SK31;SK49;SK52;SK53;SK55;SK38;SK39
Vogel et al. 2023	2023	SK28;SK4;SK30;SK31;SK47;SK32;SK6;SK49;SK34;SK51;SK12;SK53;SK38;SK40
Krishnamurthy & Harrison 2023	2023	SK4;SK47;SK6;SK11
Foltynowicz et al. 2024	2024	SK48;SK49
Bueno et al. 2024	2024	SK43;SK16;SK3;SK30;SK7;SK49;SK50;SK53;SK54;SK37;SK57;SK41;SK14
Nikitaeva et al. 2024	2024	SK30;SK46;SK18;SK20;SK21;SK55
Onu et al. 2023	2023	SK30
Lagorio & Cimini 2024	2024	SK4;SK46;SK47;SK49;SK53;SK54;SK55;SK56

B. Skills Typology for network analysis (Python input file)

Skill	Total citations	Typology H	Typology I
SK1	2	T	D
SK43	7	P	R
SK2	7	T	D
SK16	1	P	G
SK3	2	T	D
SK28	7	S	HC
SK4	11	T	D
SK44	1	P	R
SK29	3	S	HC
SK45	1	M	R
SK17	3	T	G
SK30	12	S	HC
SK31	14	S	HC
SK46	4	T	R
SK47	17	M	R
SK32	6	M	HC
SK5	6	T	D
SK6	11	T	D
SK18	1	T	G
SK48	5	M	R
SK19	3	T	G
SK7	5	T	D
SK8	5	T	D
SK9	1	T	D
SK33	5	P	HC
SK20	1	T	G
SK21	1	T	G
SK49	13	M	R
SK34	2	M	HC
SK35	4	M	HC
SK50	4	M	R
SK10	2	T	D
SK11	9	T	D
SK36	1	S	HC
SK51	12	M	R
SK22	3	P	G
SK12	9	T	D
SK52	7	M	R

Skill	Total citations	Typology H	Typology I
SK53	13	M	R
SK54	6	M	R
SK55	6	M	R
SK23	2	T	G
SK56	4	M	R
SK37	1	P	HC
SK38	8	S	HC
SK24	1	M	G
SK57	4	M	R
SK39	1	P	HC
SK25	2	T	G
SK26	2	T	G
SK40	8	S	HC
SK41	1	P	HC
SK42	3	S	HC
SK27	3	M	G
SK13	4	T	D
SK14	2	T	D
SK15	4	T	D

C. Python script

```

!pip install pyvis
import pandas as pd
from itertools import combinations
from pyvis.network import Network
import os
import pandas as pd
import networkx as nx
import matplotlib.pyplot as plt
from itertools import combinations

skills_df = pd.read_excel("data/skills.xlsx")
skills_df = skills_df[skills_df['Year'] < 2025].dropna(subset=['Skill_List'])
skills_typology = pd.read_excel("data/skills typology.xlsx")

skills_typology['Skill'] = skills_typology['Skill'].str.strip().str.lower()
skills_dict_H = dict(zip(skills_typology['Skill'], skills_typology['Typology H']))
skills_dict_I = dict(zip(skills_typology['Skill'], skills_typology['Typology I']))

skills_count = (
    skills_df['Skill_List']
    .str.split(";", expand=True)
    .stack()

```

```

.str.strip()
.str.lower()
.reset_index(drop=True)
.value_counts()
.reset_index()
.rename(columns={'index': 'Skills', 0: 'count'})
)
skills_count_dict = dict(zip(skills_count['Skills'], skills_count['count']))

skills_pairs = {}
for _, r in skills_df.iterrows():
    skills = [s.strip().lower() for s in r['Skill_List'].split(';') if s.strip()]
    for pair in combinations(skills, 2):
        skills_pairs[tuple(sorted(pair))] = skills_pairs.get(tuple(sorted(pair)), 0) + 1

result_df = pd.DataFrame(skills_pairs.items(), columns=['Skill_Pair', 'Weight'])
result_df[['First_Skill', 'Second_Skill']] = pd.DataFrame(result_df['Skill_Pair'].tolist(), index=result_df.index)
result_df.drop(columns=['Skill_Pair'], inplace=True)

for label, sd in {'H': skills_dict_H, 'T': skills_dict_I}.items():
    result_df[f'First_Skill_Typology_{label}'] = result_df['First_Skill'].map(sd)
    result_df[f'Second_Skill_Typology_{label}'] = result_df['Second_Skill'].map(sd)

result_df['First_Skill_Size'] = result_df['First_Skill'].map(skills_count_dict)
result_df['Second_Skill_Size'] = result_df['Second_Skill'].map(skills_count_dict)

result_df = result_df[result_df['Weight'] > 2].sort_values(by='Weight', ascending=False)

def draw_network_matplotlib(result_df, label, skills_dict,
                             node_font_size=9, edge_scaling=0.15,
                             figsize=(10, 7.5), layout_seed=42,
                             export_path=None):
    G = nx.Graph()

    if label == 'H':
        cmap = {"M": "#3647EB", "T": "#F58900", "S": "#FFE501", "P": "#00C87F"}
        legend_labels = {"M": "Methodological", "T": "Technical", "S": "Social", "P": "Personal"}
        typ1 = 'First_Skill_Typology_H'
        typ2 = 'Second_Skill_Typology_H'
        legend_title = "Hecklau Categorization"
    else:
        cmap = {"D": "#007BFF", "R": "#FFA726", "G": "#2E7D32", "HC": "#F8BBD0"}
        legend_labels = {"D": "Digital", "R": "Resilience", "G": "Green", "HC": "Human-Centricity"}
        typ1 = 'First_Skill_Typology_I'
        typ2 = 'Second_Skill_Typology_I'
        legend_title = "Industry 5.0 Categorization"

    for _, r in result_df.iterrows():
        for skill, size_col, typ_col in [
            (r['First_Skill'], 'First_Skill_Size', typ1),

```

```

(r['Second_Skill'], 'Second_Skill_Size', typ2]):
    if skill not in G:
        typ = skills_dict.get(skill.lower(), "Unknown")
        G.add_node(
            skill,
            size=r[size_col],
            color=cmap.get(typ, "gray"),
            typology=typ
        )
    cat1, cat2 = r[typ1], r[typ2]
    edge_color = cmap.get(cat1) if cat1 == cat2 else "#E57373"
    G.add_edge(r['First_Skill'], r['Second_Skill'],
               weight=r['Weight'],
               color=edge_color)

pos = nx.spring_layout(G, seed=layout_seed, k=3)
node_sizes = [G.nodes[n]['size'] * 100 for n in G.nodes]
node_colors = [G.nodes[n]['color'] for n in G.nodes]

plt.figure(figsize=figsize)
nx.draw_networkx_nodes(G, pos,
                       node_size=node_sizes,
                       node_color=node_colors,
                       alpha=1)

edges = G.edges(data=True)
edge_colors = [edata['color'] for _, _, edata in edges]
weights = [edata['weight'] for _, _, edata in edges]
min_w, max_w = min(weights), max(weights)
edge_weights = [
    0.5 + ((edata['weight'] - min_w) / (max_w - min_w)) * 1.8 * (10.0 - 0.5)
    if max_w > min_w else 3.0
    for _, _, edata in edges
]

nx.draw_networkx_edges(G, pos,
                      edge_color=edge_colors,
                      width=edge_weights,
                      alpha=1)

for node, (x, y) in pos.items():
    plt.text(x, y, node,
             fontsize=node_font_size,
             ha='center', va='center',
             fontweight='bold',
             bbox=dict(facecolor='white', edgecolor='black', boxstyle='round', pad=0.2))

from matplotlib.patches import Patch
handles = [Patch(color=color, label=legend_labels[key]) for key, color in cmap.items()]
handles.append(Patch(color="#E57373", label="Inter-category edge"))
plt.legend(handles=handles, title=legend_title, loc="upper right", fontsize=8)

```

```
plt.axis('off')
plt.title(f'Skill Network ({label})", fontsize=14)
plt.tight_layout()

if export_path:
    plt.savefig(export_path, dpi=300, bbox_inches='tight', format='png')
    print(f" Graph exported: {export_path}")
else:
    plt.show()

draw_network_matplotlib(result_df, 'H', skills_dict_H,
                        export_path="skill_network_H.png")

draw_network_matplotlib(result_df, 'I', skills_dict_I,
                        export_path="skill_network_I.png")
```

Journal of Industrial Engineering and Management, 2026 (www.jiem.org)



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