

Navigating the human-centric shift: A typology of workforce readiness for industry 5.0

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(article starts on next page)

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Navigating the human-centric shift: A typology of workforce readiness for industry 5.0

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ABSTRACT

The transition to Industry 5.0 requires a paradigm shift from technology-driven production to human-centric, sustainable, and resilient systems. Although the theoretical foundation of Industry 5.0 is strong, empirical evidence on the workforce readiness required for this transition remains scarce. This study addresses this gap by developing an empirical typology of workforce readiness, based on structured interviews with 160 European industrial stakeholders, using the European Commission's Industry 5.0 Learning and Assessment tool. Through cluster analysis, we identify three distinct organisational profiles: Ad hoc, Structured, and Adaptive. These clusters reveal significant diversity in how firms approach skill development, the skill levels of their workforces, and their workforce resilience. The findings show that while Structured firms have established upskilling programmes, they still lack in-demand skills such as AI literacy, whereas Ad hoc firms struggle with foundational knowledge management. The typology provides a framework for managers to develop their human-centric transition strategies and for policymakers to design targeted incentives, moving beyond generic upskilling policies.

1. Introduction

Industrial organisations worldwide face mounting pressure to transform their production systems due to geopolitical threats, sustainability imperatives, and digital technologies (World Economic Forum, 2025). While innovation in artificial intelligence, robotics, and data analytics continues to reshape manufacturing practices and organisations, their successful adoption depends not only on technological investments but also heavily on human and organisational capabilities of the workforce to integrate, adapt, and learn (Brynjolfsson, Rock, & Syverson, 2020). As innovation cycles accelerate and global competition intensifies, a workforce's ability to adapt to new circumstances and acquire new skills has become a central determinant of industrial competitiveness.

At the same time, the pace of technological change is accelerating. Recent studies suggest that a substantial share of the current workforce's skills will become obsolete within the next decade (World Economic Forum, 2025). This creates a dual challenge for organisations: one, to acquire new technical competencies, and two, to develop a learning organisation. These challenges are further intensified by demographics showing an ageing population and shrinking labour forces in many industrialised countries, which exacerbate already existing skill shortages.

These developments have led to the emergence of the Industry 5.0 paradigm, introduced by the European Commission in 2021as a complement to the technology-driven Industry 4.0. Industry 5.0 emphasises three core dimensions – human-centricity, sustainability, and resilience (Breque, de Nul, & Petridis, 2021). Within this paradigm, operators are viewed as the technology-augmented, skilled, adaptive, and value-creating key actors (Romero, Stahre, & Taisch, 2020).

Despite the growing prominence of Industry 5.0 in policy and research, empirical studies on how organisations develop workforce readiness for this transition remain limited. Existing studies predominantly focus on isolated aspects, such as digital or sustainability skills, the assessment of skill gaps, or training practices (Beducci, Acerbi, Pinzone, & Taisch, 2024; Pinzone, Fantini, & Taisch, 2023; Söderlund et al., 2024).

While some skills are automated or taken over by robots, new tasks are emerging (Acemoglu & Restrepo, 2018). The World Economic Forum estimates that 39% of the workforce's current skills will be outdated by 2030 (World Economic Forum, 2025). At the same time, demographic trends in Europe, the US, and China show an ageing

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workforce and shrinking younger generations (Statista, 2025; World Economic Forum, 2025). These developments have created major skill gaps and hinder firms' ability to adopt sustainability-driven innovation (Beducci et al., 2024; González Chávez et al., 2023). From an innovation perspective, misalignment between technological change and workforce skills can slow or halt industrial transformation (Rikala, Braun, Järvinen, Stahre, & Hämäläinen, 2024).

In particular, there is a lack of understanding of how skills, learning practices, and workforce resilience correlate within organisations undergoing transformation. Existing studies often remain on a conceptual level or focus on isolated topics such as digital or sustainability skills (Greta Braun, Rikala, Järvinen, Hämäläinen, & Stahre, 2024; Pinzone et al., 2023; Pinzone and Taisch, 2023). While these studies provide valuable insights, there is a remaining need to understand how different dimensions – skills of the workforce, learning systems, and workforce resilience – interact at the organisational level.

As a result, there is limited empirical understanding of how these dimensions combine to form distinct patterns of workforce readiness across companies. In particular, it remains unclear whether organisations follow similar patterns in their workforce readiness towards Industry 5.0 or whether their pathways diverge. This represents a critical gap, since industrial transformation is inherently systemic: organisations do not develop skills and learning practices in isolation; these efforts are directly connected to their business outcomes and workforce resilience (Brynjolfsson et al., 2020). A LinkedIn study shows that companies investing in workforce development increase employee retention, and that 94% of employees would stay at their company longer if it invests in learning (LinkedIn Learning, 2020). A gap remains in understanding how current workforce skills, skill development activities, and employee retention are linked, and how these factors manifest in organisational patterns.

To address this gap, this study develops an empirical typology of workforce readiness for Industry 5.0. Drawing on structured interview data from 160 industrial stakeholders across Europe and using the European Commission's Industry 5.0 Learning and Assessment tool, the study examines how organisations differ in their configurations of workforce skills, learning initiatives, and workforce resilience. Through cluster analysis, we identify distinct organisational profiles that reflect different approaches to preparing the workforce for human-centric, sustainable, and resilient industrial transformation.

By adopting an holistic perspective, this study moves beyond single-variable analysis and provides a broader understanding of workforce readiness. Specifically, the paper makes three contributions. First, it offers one of the first empirical typologies of workforce readiness for Industry 5.0, with a focus on skills and grounded in cross-country industrial data. Second, it conceptualises workforce readiness as a multi-dimensional organisational capability, integrating skills, organisational learning practices, and workforce resilience factors. Third, it provides actionable insights for managers and policymakers by identifying distinct readiness profiles and their associated challenges.

The study is guided by the following research questions:

- RQ1: What profiles characterise industrial organisations' workforce readiness for Industry 5.0 adoption?
- RQ2: How do skill levels, upskilling initiatives, and workforce resilience characterise these profiles?
- RQ3: What managerial and policymaking mechanisms can support organisations in improving workforce readiness across different profiles?

The remainder of the paper is structured as follows. Section 2 presents the theoretical background on Industry 5.0 and workforce-related capabilities. Section 3 outlines the research design, data collection, and analysis. Results are presented in Section 4 and discussed in Section 5. Section 6 concludes the paper and highlights directions for future research.

2. Theoretical background

The theoretical background of this study primarily focuses on the industrial transformation to Industry 5.0, the concept of workforce readiness, and the three dimensions investigated in this study, namely skills, learning systems and workforce resilience.

2.1. Industry 5.0 and the human-centric transformation

The transition from Industry 4.0 to Industry 5.0 marks a shift from a primarily technology-driven paradigm to a more human-centric and sustainable model of industrial development. While Industry 4.0 emphasised automation, digitalisation, and efficiency gains through advanced technologies such as artificial intelligence and cyber-physical systems, Industry 5.0 extends this vision by explicitly integrating human well-being, environmental sustainability, and system resilience (Breque et al., 2021; Leng et al., 2022).

In this context, the role of the workforce is fundamentally redefined. Rather than being positioned as operators of increasingly autonomous systems, workers are conceptualised as active contributors to innovation, problem-solving, and continuous improvement. Concepts such as Operator 4.0 (Romero et al., 2020) and Operator 5.0 (Romero & Stahre, 2021) highlight the integration of human capabilities with advanced technologies, enabling augmented decision-making, enhanced creativity, and safer working environments.

Much of the Industry 4.0 literature focuses on technologies and performance improvements (Forschungsunion, 2013). Still, Industry 4.0 focuses very limitedly on humans, which supports the rationale for Industry 5.0 as a promoter of human-centricity (Xu, Lu, Vogel-Heuser, & Wang, 2021). What connects the two paradigms is the enabling technologies that overlap between Industry 4.0 and Industry 5.0, such as Artificial Intelligence, Augmented Reality, Virtual Reality, Blockchain, etc. (Piccarozzi, Silvestri, Silvestri, & Ruggieri, 2024) or digital twins (Barata & Kayser, 2024). However, Piccarozzi et al. (2024) conclude that Industry 5.0 explicitly puts workers at the forefront and views technology as an enabler of lifelong learning, skill development, and the augmentation of workers' creativity. The themes discussed in the literature on Industry 5.0 include health and safety in human resources management, human-robot collaboration, and workers' skills (Piccarozzi et al., 2024).

At the same time, emerging technological frameworks, such as Human Digital Twins (Bucci, Fani, & Bandinelli, 2025), further operationalise this vision of Industry 5.0 by enabling dynamic representations of worker skills, performance, and well-being within industrial systems. These developments illustrate how technological and human-centric perspectives are increasingly intertwined in the Industry 5.0 paradigm.

2.2. Conceptualising workforce readiness for industry 5.0

The transition towards Industry 5.0 requires reconceptualising workforce readiness beyond traditional notions of technical competence. In contrast to earlier industrial paradigms, where workforce capabilities were primarily task-specific, Industry 5.0 emphasises the integration of human-centric, adaptive, and system-level capabilities (Moencks, Roth, Bohné, Romero, & Stahre, 2022). During previous technological shifts, productivity has increased only after intangibles such as skills have been put in place (Brynjolfsson et al., 2020). However, previous industrial revolutions have been driven primarily by technological implementation, resulting in productivity losses during initial transformation phases. This is often referred to as the productivity paradox (Brynjolfsson, 1993).

Industry 5.0 goes beyond traditional technical competencies and requires a combination of digital, human-centric, social, green, and resilience skills from the workforce (Pinzone et al., 2024). These include digital literacy, AI literacy, cybersecurity skills, problem-solving,

adaptability, and interdisciplinary collaboration (World Economic Forum, 2025). However, these skills are not static. The rapid technological transformation leads to a continuously changing skill demand to engage with new technical tools and systems. The interconnection between sustainability, resilience, and human-centricity requires that a sustainable system be adaptive, inclusive, and restorative, not just green (Breque et al., 2021).

Building on recent work on human-centric manufacturing systems, workforce readiness can be understood as a multi-dimensional construct that reflects the capacity of both individuals and organisations (Moencks et al., 2022) to operate effectively in complex, technology-rich, and evolving environments (Peersia, Rappa, & Perry, 2024). In particular, prior research highlights that future industrial work systems require not only advanced technical skills but also continuous learning capabilities and organisational conditions that support human well-being, adaptability, and resilience (Roth et al., 2022). From an organisational perspective, human-centricity entails a specific focus on workers' well-being, fostering inclusivity, and supporting their upskilling and other needs (European Commission, 2024). Employers can offer employees benefits that match workers' diverse needs, flexibility, upskilling and career growth opportunities, and active listening (Dhar et al., 2022).

In this perspective, workforce readiness is not limited to the presence of individual competencies but emerges from the interaction between three interrelated dimensions (Peersia et al., 2024). First, workforce skills capture the individual-level capabilities required to engage with advanced technologies, including digital and AI literacy, problem-solving, and collaborative competencies. Second, organisational learning and upskilling systems reflect the structures and processes through which these skills are developed, updated, and embedded within the organisation (Peersia et al., 2024). Third, the outcome dimension focuses on the employers' perspective on the workforce, which captures the organisation's ability to form attitudes and skills, sustain and adapt its human capital over time, including talent retention, and the capacity to respond to disruption (Peersia et al., 2024).

This conceptualisation aligns with emerging Industry 5.0 research that emphasises human-centric and adaptive production systems, in which workforce capabilities are dynamically shaped by interactions among technological infrastructures, organisational practices, and human factors (Bucci et al., 2025; European Commission, 2024). Importantly, it highlights that workforce readiness is inherently systemic: organisations do not develop skills, learning mechanisms, or resilience in isolation, but as mutually reinforcing components of broader capability configurations.

Despite this growing recognition, existing empirical studies tend to examine these dimensions separately, focusing either on skill requirements, training practices, or organisational resilience. As a result, there remains a limited understanding of how these elements combine at the organisational level to form distinct patterns of workforce readiness (Peersia et al., 2024). Addressing this gap requires an integrative approach that captures the interplay between individual and organisational capabilities.

Accordingly, this study adopts a configurational perspective, conceptualising workforce readiness as the joint manifestation of skills, learning systems, and resilience. This perspective provides the foundation for the empirical analysis, which seeks to identify distinct organisational profiles based on how these dimensions co-occur.

2.3. Organisational learning and upskilling systems

According to the Future of Jobs report (World Economic Forum, 2025), 170 million jobs are projected to be created in the next five years, while 92 million jobs will be displaced. This means workers need new skills to transition to those new jobs. Studies show that upskilling and reskilling efforts vary widely across countries in the European Union. For instance, in Bulgaria, in 2022, 0.6% of employees participated in on-the-job up- or reskilling, while in Finland, it was 20% and in Sweden, 18% of employees (PPMI & IDEA, 2025). Education providers, employers, policymakers, and employees all need to take responsibility for enhancing collaboration and closing the skill gap in industry (Greta Braun et al., 2024). Key areas for companies to consider when managing skill gaps are upskilling initiatives, empowering their workforce, measuring skill-related KPIs, having a leadership that supports a learning culture, and leveraging innovative technologies that foster learning (Greta Braun et al., 2025). However, not all companies have established upskilling systems, while other do have learning systems to offer to their employees (Greta Braun et al., 2025).

To bring the organisation forward in terms of skills, the actual skill gap has to be identified. A skill gap is the difference between the skills employers expect of their employees and the skills those employees actually possess (Rikala et al., 2024). However, measuring skill gaps (Rikala et al., 2024). In a CECIMO study (Hunchak, 2025), 47% of companies reported that partnerships with education are part of their efforts to retain staff. On the positive side, there is motivation among workers to thrive in the work of the future. 72% of workers globally feel "excited about opportunities to learn and grow" in their role, and 77% feel "ready to adapt new ways of working" (PWC, 2024). However, around half of workers globally find it hard to keep up with the changes happening in parallel (PWC, 2024). Due to limited resources, smaller companies face greater challenges in upskilling their workforce (Hunchak, 2025). For instance, 40% of manufacturing companies don't have a digital learning system (Dhar et al., 2022).

2.4. Towards a configurational perspective of workforce readiness

Taken together, workforce skills, organisational learning systems, and workforce resilience represent interrelated dimensions of workforce readiness for Industry 5.0. This suggests that companies may face different challenges and patterns of readiness, depending on how these elements are combined. For example, some companies may possess strong technical skills but lack structured learning systems. To capture these differences, a configurational approach is required. By analysing how multiple dimensions co-occur within organisations, it becomes possible to identify distinct profiles of workforce readiness. This perspective moves beyond single-variable analysis and provides a more holistic understanding of how organisations prepare for Industry 5.0 transformation.

3. Methodology

This study adopts an exploratory quantitative research design to identify patterns in organisational workforce readiness for Industry 5.0. Given the limited availability of empirical typologies in this domain, a configurational approach was employed to uncover naturally occurring groupings of organisations based on their workforce-related capabilities. Cluster analysis was selected as it enables the identification of homogeneous subgroups within heterogeneous samples, supporting the development of empirically grounded typologies (Cooper & Schindler, 2014).

The analysis focuses on organisational-level configurations of three interrelated dimensions: (1) workforce skills, (2) learning and upskilling practices, and (3) workforce resilience. These dimensions jointly reflect workforce readiness as conceptualised in the Industry 5.0 paradigm.

3.1. The industry 5.0 learning and assessment tool

Data collection was conducted using the European Commission's Industry 5.0 Learning and Assessment tool, an instrument designed to learn about and assess organisational performance across the three core dimensions of Industry 5.0: human-centricity, sustainability, and resilience.

The tool comprises 119 questions organised into three pillars and further structured along the input, process, and output dimensions of

industrial systems. In addition, it captures contextual information about the organisation, including its size, sector, and the respondent's role.

The European Commission's Directorate-General for Research and Innovation led the tool's development through an iterative, collaborative process. The team developed an initial version using existing policy frameworks and assessment approaches, including the Corporate Sustainability Reporting Directive (CSRD), the EU Taxonomy for sustainable activities, and the Social Economy Canvas developed by the Joint Research Centre. The tool was then refined through a series of workshops with members of the Industry 5.0 Community of Practice from November 2023 to May 2024.

Given this development process, the tool offers a policy-informed, practice-oriented perspective on Industry 5.0 readiness rather than a formally validated psychometric scale. However, its design integrates established concepts of workforce skills, organisational learning, and resilience, making it suitable for exploratory empirical analysis.

In this study, the full instrument was used for data collection, while a subset of workforce-related items was selected for clustering analysis (see Section 3.4). Example questions are shown in Fig. 1.

3.2. Data collection and sample

Data were collected through structured interviews using the European Commission's Industry 5.0 Learning and Assessment tool. The tool comprises 119 questions covering the three pillars of Industry 5.0: human-centricity, sustainability, and resilience.

A total of 160 respondents participated in the study, representing industrial organisations across 20 European countries. Respondents included managers (45%), employees (41%), and organisational representatives (14%). The sample includes firms of varying sizes and sectors, with a concentration in Sweden (29%), Germany (19%), and Italy (18%).

A combination of purposive and convenience sampling was used, supported by snowball recruitment and professional networks. While this approach enabled access to relevant industrial stakeholders, it may introduce self-selection bias, as organisations more engaged with Industry 5.0 topics may be overrepresented. This limitation is acknowledged and discussed in Section 5.

3.3. Interview process

Data were collected via video-call interviews. This approach was chosen to ensure consistent interpretation of questions and to reduce response errors in a complex, multi-dimensional assessment tool. During the interviews, the interviewer read each question aloud, clarified terminology where needed, and recorded responses directly into the survey system.

While this guided approach improves response quality and completeness, it may introduce interviewer bias. To mitigate this risk, interviewers followed a standardised protocol and limited their role to clarification rather than interpretation. No leading prompts were provided. However, at the end of each interview, the respondent had the opportunity to provide additional feedback on the tool.

3.4. Variable selection and data preparation

Although the assessment tool includes 119 items, this study focuses on a subset of 19 questions directly related to workforce capabilities. The selection of these 19 questions was guided by two criteria: (1) conceptual relevance to workforce readiness, and (2) alignment with the three focused dimensions – skills, learning practices, and workforce resilience. This selection was done using the thematic analysis of the tool questions, organised in a table in which every tool question was tagged with the pillar (human-centricity, sustainability, resilience), input/process/output type, and a label describing the specific organisational capability.

Using this taxonomy, we included every item whose capability tag corresponds to (i) individual workforce skills, (ii) organisational learning and training practices, or (iii) workforce-related capability outcomes – regardless of which pillar the item was formally filed under. Specifically: all ten items tagged with Workforce skills (Q3–Q12), corresponding to the instrument's dedicated skilled/knowledgeable-workforce question block; six items capturing learning and training capacity – the two Learning organisation items (Q24, Q26), the knowledge-management technology item tagged Human-centric technology adoption (Q18), and every other training-specific item in the full 119-item instrument regardless of pillar: sustainability training (Q62), cybersecurity training (Q102), and digital-skills training (Q106); and three items capturing workforce outcomes – staff retention and talent attraction, tagged Social outcomes (Q47, Q48), and critical-skill redundancy, tagged Organisational resilience (Q82).

This selection deliberately cuts across the instrument's three pillars because workforce capability, as conceptualised in this study (Section 2.2), is not confined to the human-centricity pillar: the instrument itself places sustainability-, cybersecurity-, and digital-skills-training items within the sustainability and resilience pillars, even though conceptually they are training activities identical in kind to the human-centricity learning items. Selecting by capability tag rather than by pillar therefore captures the full breadth of workforce-relevant items available.

The excluded 100 items address organisational capabilities outside this scope: environmental management, sustainable operations, and environmental-impact monitoring (27 items, sustainability pillar); financial, supply-chain, cybersecurity/digital infrastructure, and innovation/IP resilience (36 items, resilience pillar); and human-centric technology design, employee well-being, customer/community engagement, and strategic vision/diversity items not specific to skills or learning (37 items, human-centricity pillar). We acknowledge some of these – particularly technology-adoption and organisational-resilience items – may hold complementary insight into workforce readiness not captured here.

The full list of selected items is provided in Table 1, while the complete questionnaire is included in the Appendix.

Responses were collected using ordinal categories ("Yes", "Partially", "No", "I don't know", and "Not applicable"). For quantitative analysis, the first three categories were encoded numerically (Yes = 3, Partially = 2, No = 1), reflecting an ordered scale of increasing organisational capability. This encoding preserves the ordinal nature of the responses while enabling distance-based clustering.

The categories "I don't know" and "Not applicable" were not

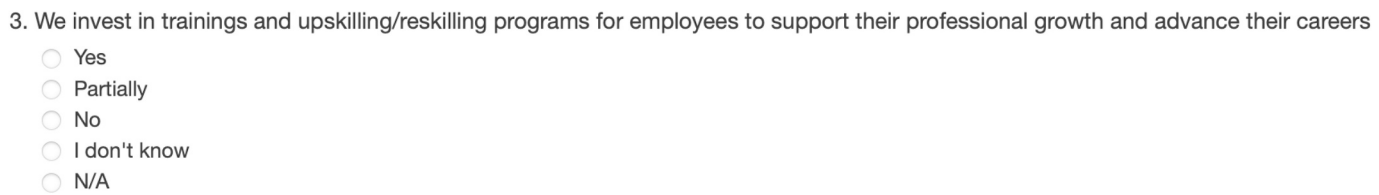


Fig. 1. Example from survey (Question Q26).

Table 1
Selected questions for clustering.

Question number in survey	Question content	Category
Q3	Digital literacy, develop new digital manufacturing systems	Current skills of the workforce
Q4	AI literacy	
Q5	Creative problem solving	
Q6	Entrepreneurial mindset	
Q7	Work physically and psychologically safely	
Q8	Inter-cultural and inter-disciplinary inclusive mindset	
Q9	Cybersecurity	
Q10	Handle complexity	
Q11	Communicate with humans, IT, AI	
Q12	Open-mindedness towards constant change, transformation skills	
Q18	Knowledge management	Learning initiatives
Q24	Learning organisation model	
Q26	Training, upskilling, reskilling programs	
Q62	Training for sustainability skills	
Q102	Cybersecurity training	
Q106	Digital skills training	
Q47	Reduced staff-turnover, improved retention	Workforce resilience
Q48	Attract top talent	
Q82	Critical skills redundancy	

interpreted as low performance but as a lack of information or contextual irrelevance. Accordingly, these responses were treated as missing values. To retain observations for clustering, missing values were imputed using mean imputation at the variable level, replacing missing entries with the sample mean for each variable.

This approach ensures that organisations are not systematically penalised for lack of knowledge or for questioning the inapplicability, while preserving the overall distribution of responses. However, mean imputation may reduce variance and hide extreme values, a limitation acknowledged in the analysis.

3.5. Measurement considerations

The variables used in this study are drawn from the European Commission's Industry 5.0 Learning and Assessment tool, developed through a collaborative, policy-driven process rather than formal psychometric scale construction. Consequently, the instrument does not provide established measures of internal consistency (e.g., Cronbach's alpha), and the selected subset of items has not been previously validated as a unified scale.

Instead of serving as reflective indicators of a single latent construct, the selected variables represent conceptually related yet distinct organisational capabilities across three dimensions: workforce skills, learning and upskilling practices, and workforce resilience. For example, the skills dimension encompasses competencies such as digital literacy, AI literacy, problem-solving, and communication abilities. These competencies are not expected to co-vary strongly as a single factor, but collectively, they describe the breadth of workforce capabilities relevant to Industry 5.0.

Given this heterogeneity, the study adopts a configurational perspective, analysing variables jointly to identify patterns of organisational characteristics rather than measuring a single underlying construct. In this context, internal consistency metrics such as Cronbach's alpha have limited interpretive value, as high inter-item correlation is neither expected nor required.

The validity of the selected variables is therefore grounded primarily in face validity and in conceptual alignment with the Industry 5.0 framework. The included items directly reflect key competencies and organisational practices emphasised in prior literature and policy documents, such as digital and AI literacy, continuous learning systems, knowledge management, workforce adaptability, and talent retention. The selected questions map onto capability themes identified through thematic analysis, confirming that the capabilities are related but distinct.

In addition, the between-cluster significance testing reported in Section 3.6.3 shows that most items (16 of 19) differentiate the derived organisational profiles independently — a pattern more consistent with a multi-dimensional capability set than with a tightly unidimensional scale, for which Cronbach's alpha would in any case be the more natural diagnostic. We nonetheless maintain, as noted above, that we did not perform formal psychometric validation of the instrument, and this remains a limitation of this exploratory study. The lack of formal psychometric validation means we cannot fully rule out measurement error and construct overlap. Second, using a reduced subset of items (19 out of 119) may omit relevant aspects of workforce readiness captured by the full instrument. Third, the variables rely on self-reported organisational assessments, which may introduce subjective bias.

These limitations are recognised as inherent to exploratory research on emerging policy instruments and are discussed further in Section 5. Despite these constraints, the selected variables provide a comprehensive, policy-relevant representation of workforce readiness dimensions and support the identification of meaningful organisational patterns.

3.6. Clustering method

3.6.1. Choice of clustering technique

K-means clustering was employed to identify groups of organisations with similar workforce capability profiles. K-means partitions observations into k clusters by minimising within-cluster variance using Euclidean distance (Cooper & Schindler, 2014).

The use of K-means with ordinal Likert-type data requires careful consideration, as the method assumes continuous variables (Cooper & Schindler, 2014). However, prior research in management and operations has shown that K-means can produce robust and interpretable results when applied to ordinal data (Acito, 2023), particularly when the objective is exploratory pattern detection rather than precise distance estimation (Arioli et al., 2025).

To address potential limitations, the results are interpreted as approximate groupings rather than exact metric-based classifications, and robustness checks are incorporated (see Section 3.6.3).

3.6.2. Determination of number of clusters

The optimal number of clusters was determined using the elbow method, which evaluates the within-cluster sum of squares (WCSS) across different values of k. The elbow plot (Figure X) shows a clear inflection point at $k = 3$, indicating diminishing returns in variance reduction beyond this point.

This result is consistent with the emergence of three distinct and interpretable organisational profiles, supporting the selection of a three-cluster solution.

3.6.3. Robustness check of clustering

To check the robustness of the 3-cluster K-means solution, we performed four complementary robustness and validity checks along four dimensions, comprising seven statistics in total (Table 2): (i) internal validity indices, (ii) agreement with two alternative clustering algorithms, (iii) stability under re-initialisation, and (iv) statistical significance of between-cluster differences.

First, cluster validity indices were computed: the silhouette score (0.116), Davies-Bouldin index (2.341), and Calinski-Harabasz index (19.5) indicate modest rather than strongly separated cluster structure, which is often seen when clustering ordinal (1–3) variables. Ordinal data constrains the geometric separation achievable in the score space, and is an expected characteristic of exploratory typologies built on Likert-type organisational data.

Table 2
Robustness and validity check.

Purpose	Metric	Value	Explanation
Internal validity	Silhouette score	0.116	Modest separation (normal for clustering in ordinal scale (1,2,3) instead of continuous measurements, so the scores don't have enough room to separate cleanly
	Davies-Bouldin index	2.341	
	Calinski-Harabasz index	19.500	
Agreement with alternative algorithms	ARI (K-means vs K-medoids)	0.230	Moderate to quite low agreement (different algorithms are landing on a bit different partitions)
	ARI (K-means vs Hierarchical/ Ward)	0.187	
Initialisation stability	Mean ARI across 100 reseeds	0.866	K-means clustering is internally reproducable, regardless of starting point
Significance testing	Kruskal-Wallis	16 of 19 significant	Whichever partition K-means lands on, it's clustering organisations into groups that differ significantly in 16 out of 19 capability variables, even under a conservative Bonferroni correction

Second, we compared the K-means partition with two alternative algorithms applied to the same data: K-medoids (Cooper & Schindler) and Ward's hierarchical clustering. Agreement, measured via the Adjusted Rand Index, was moderate to low (ARI = 0.230 for K-medoids; ARI = 0.187 for hierarchical clustering), indicating that exact partition boundaries are sensitive to the clustering algorithm and its underlying optimisation criterion. This sensitivity is a known characteristic of applying distance-based methods that each optimises a different internal criterion (squared Euclidean distance to centroids for K-means, absolute distance to representative data points for K-medoids, minimum-variance agglomeration for Ward's method) to ordinal data. Our approach was exploratory rather than intended to confirm an exact typology (Section 3.5).

Third, we assessed the stability of the K-means solution by refitting the model with 100 different random initialisations. The mean Adjusted Rand Index across reseeds was high (0.866, SD = 0.103), indicating the algorithm reliably converges to the same three-cluster structure regardless of starting point. This means the reported typology is not an artefact of a particular initialisation, even though it diverges somewhat from partitions produced by other algorithms.

Fourth, and most directly relevant to whether the clusters represent meaningfully different organisational profiles, we conducted Kruskal-Wallis tests for each of the 19 variables across the three clusters, with a Bonferroni-corrected significance threshold ($\alpha = 0.05/19 \approx 0.0026$). Sixteen of nineteen variables differed significantly across clusters at this conservative threshold; only creative problem-solving (Q5), critical skill redundancy (Q82), and staff turnover/retention (Q47) did not reach significance. This indicates that, whatever precise partition K-means converges to, the resulting clusters differ substantively on the large majority of workforce-capability dimensions, which is the central empirical basis for the proposed typology.

To summarise, these results support a qualified robustness claim: the K-means solution is internally reproducible and yields statistically meaningful group differences, but its precise partition boundaries show some sensitivity to algorithm choice. We report this transparently as a limitation of the exploratory approach (Section 5.3) and identify latent class analysis designed explicitly for categorical/ordinal indicators as a natural confirmatory extension for future work.

3.7. Cluster interpretation

Following clustering, each organisation was assigned to one of three clusters. Cluster profiles were analysed by examining mean scores across variables and comparing patterns across the three dimensions.

Clusters were labelled inductively based on their dominant characteristics, resulting in three organisational profiles: Ad hoc, Structured, and Adaptive. These labels are descriptive and aim to capture differences in how organisations configure workforce capabilities, rather than implying a strict performance hierarchy.

In addition to variable-level analysis, cluster distributions were examined across organisational characteristics, such as firm size and type, to provide further contextual interpretation of the results.

4. Results

The clustering analysis resulted in a three-cluster solution, as supported by the elbow method (Fig. 2), which indicated a clear inflection point at k = 3. This suggests that a three-cluster configuration balances within-cluster homogeneity and model parsimony.

The three clusters represent distinct organisational configurations of workforce readiness and are labelled as Ad hoc, Structured, and Adaptive, based on their dominant characteristics.

4.1. Sample characteristics

The study included 160 participants from various industrial companies across Europe. The respondents represented diverse organisational sizes, countries, and industrial ecosystems. 45% of participants were managers in industrial companies, 41% were individuals/employees in industrial companies, and 14% represented an organisation (see Table 3).

The participants came from 20 EU member states, ensuring extensive geographical coverage, including Sweden, Germany, France, the Netherlands, Italy, Estonia, Slovenia, Ireland, Spain, Belgium, Denmark, Lithuania, Bulgaria, and Austria, see Table 3.

4.2. Cluster profiles

The cluster profiles are derived from the mean scores of the 19 variables across the three dimensions: workforce skills, learning and upskilling practices, and workforce resilience. Fig. 3 provides a visual comparison of the clusters, while Table 4 summarises the scores across dimensions.

Some similarities between clusters are evident in the spider diagram. All three clusters score lower on AI and entrepreneurial skills. At the same time, they all score higher in digital and creative problem-solving skills, as well as in the ability to work safely, both physically and psychologically. Additionally, all three clusters score lower in sustainability training and knowledge management. By contrast, all three clusters

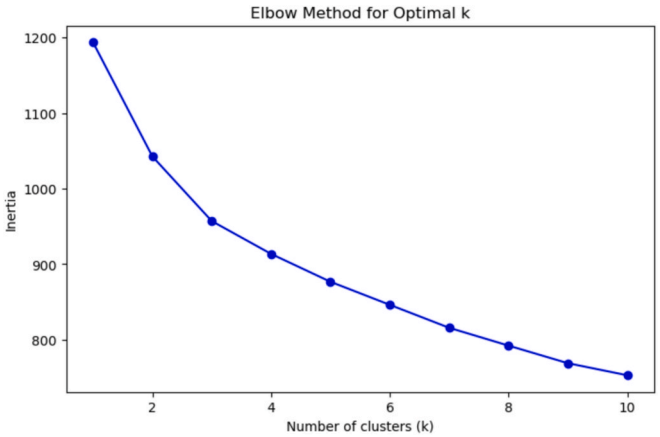


Fig. 2. Elbow method for optimal number of clusters.

Table 3
Sample characteristics.

Company's characteristics	Percentage
Country	
Sweden	29%
Germany	19%
Italy	18%
Spain	6%
Slovenia	5%
Ireland	4%
France	3%
Netherlands	3%
Portugal	3%
Denmark	2%
Estonia	1%
Other (Finland, Austria, Belgium, Bulgaria, Czechia, Greece, Latvia, Lithuania, Poland)	6%
Type of organisation	
SME	49%
Big industry	38%
Startup	12%
Other	1%
Public research organisation	1%
Company size	
Mid-cap business (250–3000 employees)	26%
Small business (10–50 employees)	24%
Large business (min 3000 employees)	20%
Medium-sized business (50–250 employees)	16%
Micro business (max 10 employees)	14%
Industrial ecosystem	
Digital	18%
Health/Life Sciences	13%
Mobility-Transport-Automotive	12%
Manufacturing	11%
Retail	6%
Construction	6%
Agri-food	6%
Energy-renewables	5%
Process/Chemical	5%
Electronics	4%
Aerospace and defence	4%
Energy-intensive industries	3%
Textile	1%
Other	7%

score higher on the question regarding training, upskilling, and reskilling programmes.

Table 4 shows the mean score per cluster for each dimension.

The distribution of company size across the three clusters shows the highest number of Micro and Small businesses in Cluster "Adaptive", with 52 respondents (see Fig. 4). Cluster "Ad hoc", with 25 respondents, is dominated by mid-cap and large businesses. Cluster "Structured", comprising 83 respondents, includes companies of all sizes. The distribution of company size is also reflected in the distribution of organisational types, as shown in Fig. 5. Most startups are in Cluster "Adaptive", and most big industry companies are in Cluster "Ad hoc". SMEs are distributed across all clusters but are more prevalent in Cluster "Structured" and Cluster "Adaptive". The analysis of other company metadata reveals no notable patterns across the different characteristics and is therefore not presented here.

To summarise, the "Structured" cluster exhibits the highest scores in nearly all areas, particularly in AI literacy, communication, openness to change, and training investments. "Ad hoc" lags in most dimensions, except in question Q7 on working physically and psychologically safely. "Adaptive" demonstrates strengths in entrepreneurial skills, an inclusive mindset, openness to change, managing complexity, and communication, but lacks systematic training in AI and cybersecurity skills.

Based on their learning capabilities, the clusters are referred to as "Ad hoc, Structured, and Adaptive". These labels are descriptive and do not imply a performance ranking. The first cluster is called "Ad hoc" because of the indications that its skill management is reactive rather than strategically planned. The "Structured" cluster derives its name from its presence of knowledge management and the provision of upskilling programmes for its employees. The "Adaptive" cluster comprises agile companies that, despite limited resources, achieve high skill levels. Additionally, the "Adaptive" cluster's workforce is adept at adapting to constant change.

4.2.1. *Cluster "Ad hoc"*

The "Ad hoc" cluster is characterised by consistently low scores across all three dimensions of workforce readiness. Organisations in this cluster exhibit limited development of workforce skills, with particularly low scores in digital literacy, AI literacy, and problem-solving capabilities. Learning and upskilling practices are largely informal or absent, with minimal investment in structured training programs or knowledge management systems.

In terms of workforce resilience, these organisations show weak performance, including challenges in talent attraction and retention, as well as limited redundancy of critical skills. The overall pattern suggests a reactive approach to workforce development, where capabilities are not systematically cultivated but emerge in an ad hoc manner.

4.2.2. *Cluster "Structured"*

The "Structured" cluster is characterised by relatively high scores in learning and upskilling practices, reflecting the presence of formalised training programs, knowledge management systems, and organisational learning structures. Organisations in this cluster demonstrate a clear commitment to workforce development through systematic investments in training and skill-building initiatives.

However, this cluster exhibits a more uneven profile across dimensions. While learning systems are well developed, workforce skills—particularly in emerging areas such as AI literacy and advanced problem-solving—remain moderate. Moreover, workforce resilience indicators, such as talent retention and skill redundancy, are comparatively weaker than expected given the level of investment in training.

This configuration suggests that while organisations in the "Structured" cluster have established formal mechanisms for capability development, these do not always translate into fully embedded or resilient workforce capabilities.

4.2.3. *Cluster "Adaptive"*

The "Adaptive" cluster demonstrates consistently high scores across all three dimensions, representing the most advanced level of workforce readiness. Organisations in this cluster exhibit strong workforce skills, including digital and AI literacy, as well as high levels of adaptability, problem-solving, and communication capabilities.

In addition, these organisations have well-developed learning systems, characterised by continuous upskilling, effective knowledge management, and the integration of learning into daily operations. Workforce resilience is also strong, with high levels of talent attraction and retention, as well as redundancy in critical skills.

The overall pattern reflects a proactive and integrated approach to workforce development, where skills, learning systems, and resilience mutually reinforce each other. This enables organisations to adapt effectively to technological and organisational change.

4.3. *Comparative analysis of clusters*

A comparison of the three clusters reveals distinct patterns in how organisations differ in workforce readiness.

- The "Ad hoc" cluster represents organisations with limited and fragmented capability development across all dimensions.

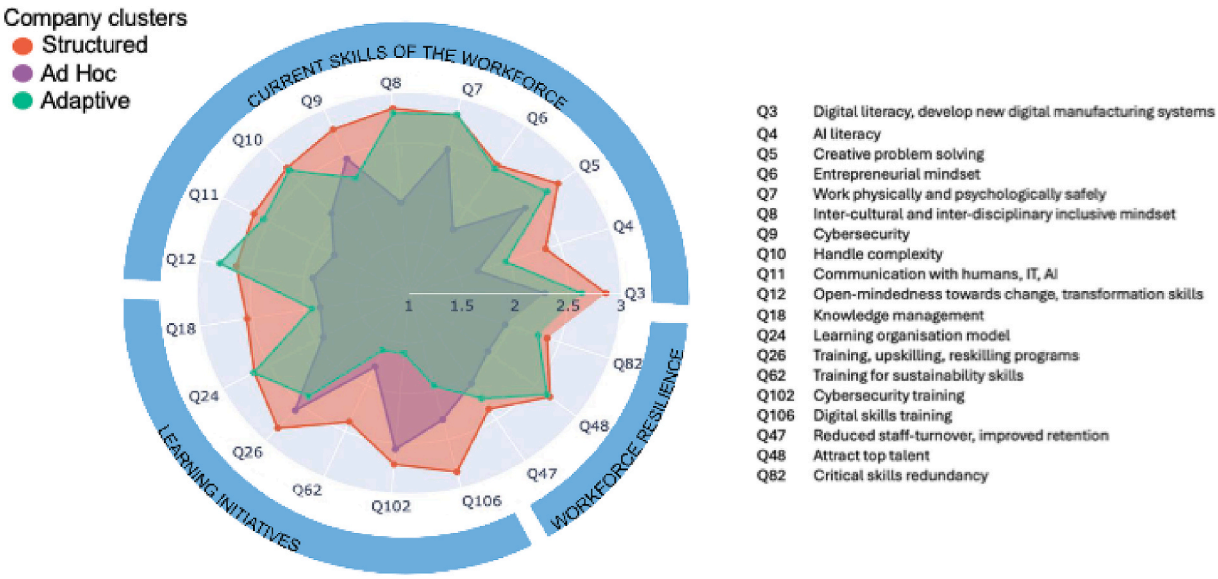


Fig. 3. Cluster profiles by question responses.

Table 4
Mean score per cluster for each dimension.

Dimension	AD HOC (N = 25)	Structured (N = 83)	Adaptive (N = 52)
Current skills of the workforce	2.08	2.7	2.56
Learning initiatives	2.17	2.66	2.03
Workforce resilience	1.99	2.48	2.4

- The "Structured" cluster reflects organisations that have invested in formal learning systems but have not fully translated these investments into resilient and adaptive workforce capabilities.
- The "Adaptive" cluster represents organisations that have achieved a balanced and integrated configuration of skills, learning, and resilience.

This qualitative similarity is confirmed statistically: creative problem-solving (Q5) is the only workforce-skills item that does not differ significantly across clusters after Bonferroni correction ($H = 8.50$, $p = 0.014$, ns at $\alpha = 0.0026$), consistent with the uniformly high scores observed across all three profiles.

Interesting to note is that two of the three workforce resilience indicators do not differentiate the clusters statistically: staff turnover/retention (Q47: $H = 3.64$, $p = 0.162$) shows no evidence of difference across profiles, and critical skill redundancy (Q82: $H = 7.24$, $p = 0.027$) is only nominally significant and does not survive Bonferroni correction. Only talent attraction (Q48: $H = 23.09$, $p < 0.001$) significantly differentiates the clusters. This pattern indicates that pronounced differences in skills and training investment across clusters (Section 4.1) do not translate into correspondingly differentiated resilience outcomes – a finding that generalises, rather than being confined to, the "Structured paradox" discussed in Section 5.1.2.

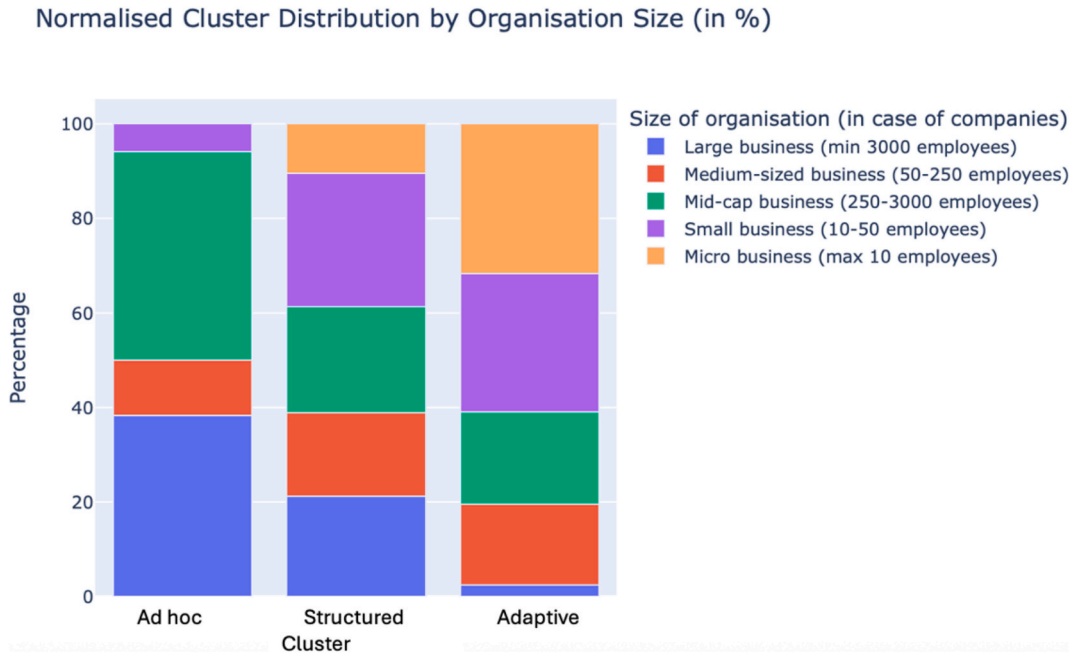


Fig. 4. Normalised cluster distribution by organization, size in %.

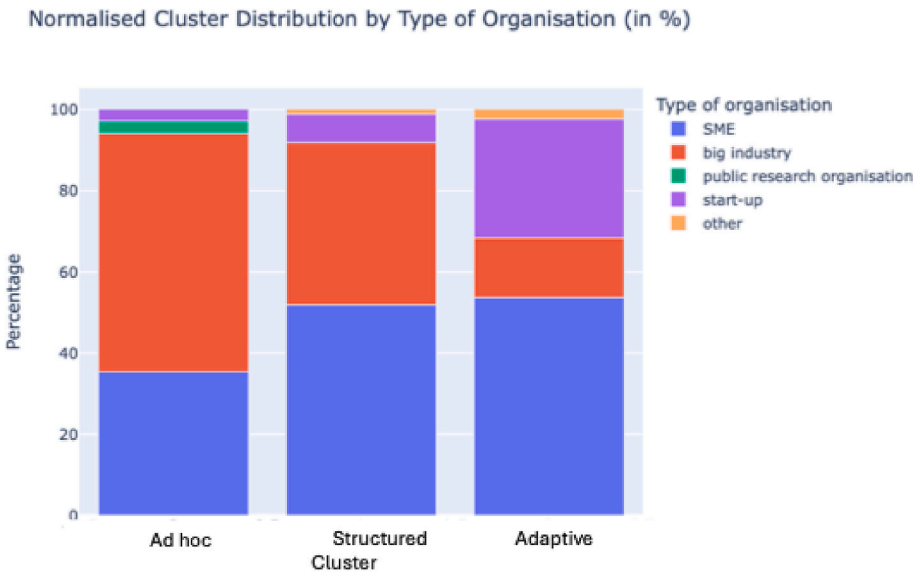


Fig. 5. Normalised cluster distribution by type of organisation in %.

The differences between clusters are not limited to individual variables, but reflect systematic variations across the three dimensions.

4.4. Typology of workforce readiness for Industry 5.0

Based on the cluster analysis, we propose a typology of workforce readiness for Industry 5.0, see Table 5.

This typology provides a structured overview of how organisations differ in their approach to workforce readiness. Rather than representing a single characteristic, the clusters reflect qualitatively different capability configurations, each with distinct strengths and challenges.

In the following section, the typology forms the basis for discussions of managerial and policy implications.

Table 5
Cluster characteristics.

Cluster	Core characteristics	Strengths	Weaknesses	Overall readiness profile
Ad hoc	Low skills, weak learning systems, low resilience	Flexibility, potential for rapid change, upskilling and reskilling programs (cybersecurity training)	Lack of structure, limited capability development	Reactive, unstructured readiness
Structured	Strong formal learning systems, moderate skills, weaker resilience	Systematic training and knowledge management	Limited adaptability and retention, despite learning investments	Process-driven but not fully embedded readiness
Adaptive	High skills (except cybersecurity and AI), learning systems, but weak knowledge management, high resilience	Integrated and continuous capability development	Resource-intensive to maintain, limited training in digital and sustainability skills	Proactive, integrated readiness

5. Discussion

This study analysed how industrial firms differ in their workforce readiness for Industry 5.0, by examining configurations of skills, learning initiatives, and the workforce through structured interviews with 160 practitioners across European industry. Rather than focusing on individual skill gaps, the analysis identified distinct workforce-related capabilities and combined them into profiles.

The findings map onto the study's three research questions. RQ1 (which profiles characterise organisations' workforce readiness) is answered by the three-cluster typology developed in Section 4.4 (Ad hoc, Structured, Adaptive). RQ2 (how skills, upskilling, and resilience characterise these profiles) is answered by the comparative analysis across clusters in Section 4.2. RQ3 (what managerial and policy mechanisms support improvement) is answered by the cluster-specific recommendations in this section and synthesised in Section 5.4.

5.1. Interpreting workforce readiness as configurations

Based on their dominant workforce readiness characteristics, the clusters are referred to as “Ad hoc, Structured, and Adaptive”. The labels are descriptive and do not imply a maturity ranking, while readily capturing differences in workforce readiness for Industry 5.0.

Our approach addresses a gap identified in prior research, where skills, training, and resilience dimensions typically have been studied separately. By demonstrating how these dimensions relate in practice, the study provides an holistic understanding of workforce readiness in contemporary global industry.

5.1.1. Ad hoc

Organisations in the “Ad hoc” configuration exhibit foundational human-centric capabilities, with limited formalisation of learning initiatives and fragmented approaches to skill development. Although there is basic awareness of skill gaps, our study show that upskilling activities tend to be reactive rather than systematically integrated into organisational routines.

The dominance of large and mid-cap businesses can be seen to reflect general inertia among industrial companies with such characteristics. This stagnation aligns with the productivity paradox described in literature (Brynjolfsson, 1993), highlighting how investments in digital technologies do not automatically translate into improved performance without complementary investments in skills, organisational change,

and culture (Brynjolfsson et al., 2020).

From a managerial perspective, these findings suggest that improving workforce readiness requires not only increased investment in training but also the establishment of clear organisational structures for skill development (World Economic Forum, 2025). This includes defining responsibility for workforce development, systematically identifying skill gaps, and embedding learning into organisational practices. In addition, fostering psychological safety and leadership committed to learning may support the transition from reactive to proactive capability development (Greta Braun et al., 2025).

Finally, the limited use of advanced tools for skill management suggests an opportunity for leveraging AI-based systems to support capability development. Such tools can facilitate the identification of skill gaps and enable more targeted and individualised learning pathways (Braun et al., 2024).

5.1.2. Structured

Organisations in the "Structured" configuration exhibit the highest level of formalisation in workforce development, characterised by well-established training programmes, knowledge management systems, and systematic upskilling. These organisations also perform strongly across many skills, except AI skills. However, despite these strengths, the results reveal a notable paradox: high investment in learning systems does not fully translate into corresponding levels of workforce resilience. In particular, indicators such as talent retention and redundancy of critical skills remain comparatively underdeveloped. This mismatch suggests that formalised learning structures alone cannot ensure adaptive, resilient workforce capabilities. Statistical testing confirms this decoupling is not unique to the Structured cluster: staff turnover/retention and critical skill redundancy fail to differentiate any of the three profiles (Section 4.3), indicating that the gap between capability investment and workforce resilience is a pattern across the sample rather than a Structured-specific anomaly.

We note a potential inconsistency: organisations that excel at implementing training systems may still struggle to embed these capabilities effectively within their workforce. From a resource-based perspective, this highlights the difference between resource availability and organisational integration. Without such integration, investments in learning may not be impactful. The challenge of adopt new knowledge in the company to actually make use of it can be explained by the concept of absorptive capacity which notes that companies who have missed to built an expertise in certain area early-on may have missed that adoption requires organisational routines as a complement (Brynjolfsson et al., 2020; Cohen & Levinthal, 1990). These results could also suggest that larger firms struggle more to navigate technological change, since their businesses span more areas and become more complex. A recent report by ManpowerGroup (ManpowerGroup, 2026) reveals that large firms experience the most severe talent shortages, meaning that these companies (1000–4999 employees), who are likely to have the most advanced resources for talent acquisition, still struggle the most (75% of the interviewed companies) with hiring.

The findings resonate with prior research on technologically advanced organisations, which shows that formal maturity does not necessarily imply adaptability (Romero & Stahre, 2021). Similar studies on organisational resilience emphasise that resilience emerges not only from structured processes but also from the dynamic interplay among anticipation, coping, and adaptation mechanisms (Chari et al., 2024).

One possible explanation is that formalisation itself may introduce rigidity in organisations. Highly structured organisations often rely on standardised processes and hierarchical decision-making, which can limit employee autonomy and reduce opportunities for experiential learning and knowledge sharing. This may impair developments of transformation skills.

From a managerial perspective, our findings suggest that organisations in the "Structured" cluster benefit from shifting focus from the provision of training to integration and application of learning. This includes linking learning outcomes to strategic objectives, embedding skill development into daily work, and fostering continuous feedback mechanisms (Greta Braun et al., 2025). Further, the use of AI-enabled skill management (Fareri, Apreda, Mulas, & Alonso, 2023) may support more dynamic and individualised skill development (G. Braun et al., 2024).

Overall, the "Structured" cluster illustrates that workforce readiness for Industry 5.0 requires not only well-designed learning systems, but also the organisational conditions necessary to translate these systems into adaptive and resilient capabilities.

5.1.3. Adaptive

Organisations in the Adaptive configuration exhibit a distinct pattern of workforce readiness characterised by flexibility, openness to change, and strong transformation capabilities. Adaptive primarily comprises startups and small businesses, with moderate scores across most skills, but excels in open-mindedness and transformation capabilities.

Unlike Structured cluster, Adaptive firms rely less on formalised training systems and instead appear to integrate learning into ongoing work practices. This informal and practice-based approach to capability development aligns with the agile nature of smaller organisations.

However, this flexibility comes with important trade-offs. The results indicate comparatively lower levels of technical capabilities, particularly in areas such as AI literacy, cybersecurity, and knowledge management.

This configuration reflects a tension between agility and fragility. While Adaptive organisations benefit from speed, vision-driven leadership, and a strong capacity for transformation, they are also vulnerable to skill shortages. This is consistent with research on startups and small firms, which highlights challenges related to limited financial resources, short-term survival pressures, and the risk of failing to scale (Dhar et al., 2022; Hunchak, 2025).

At the same time, the strengths of Adaptive organisations should not be underestimated. Their ability to attract motivated talent and foster innovation makes them a potential leader in human-centric transformation. In some respects, their informal and flexible structures resemble adaptive resilience (Ivanov, 2022).

From a managerial and policy perspective, the key challenge for Adaptive organisations is to maintain their agility while building more robust and scalable capabilities. This may involve selectively introducing structured training initiatives, strengthening knowledge management practices, and leveraging external partnerships to save resources. Collaboration with larger firms or publicly funded upskilling programmes may provide pathways to overcome resource limitations.

Overall, the Adaptive configuration highlights that workforce readiness for Industry 5.0 does not require full formalisation, but does require a balance between flexibility and capability development.

5.2. Implications for industry 5.0 transformation

The typology developed in this study has important implications for both theory and practice. From a theoretical perspective, it advances understanding of workforce readiness as a multidimensional and configurational construct. Rather than conceptualising readiness as a linear progression, the findings highlight distinct pathways through which organisations develop workforce capabilities.

From a managerial perspective, the results suggest that different organisational profiles require distinct strategies:

- Ad hoc organisations need to establish foundational structures for workforce development, including basic training programs and knowledge management systems.
- Structured organisations should focus on translating formal learning systems into embedded capabilities, for example, by integrating training with daily work practices and fostering a culture of continuous learning.

- Adaptive organisations demonstrate the benefits of an integrated approach, where skills, learning systems, and resilience reinforce each other. However, maintaining this configuration may require sustained investment and organisational alignment.

These findings also have policy implications, particularly for Industry 5.0 initiatives. Policymakers should recognise that organisations are at different stages of readiness and may require tailored support, ranging from basic capability-building to advanced innovation and resilience strategies.

5.3. Discussion of methodological approach

This study employed a quantitative approach, collecting interview data using the Industry 5.0 Learning and Assessment tool (Greta; Braun & Angione, 2025). Although this tool captures several elements related to human-centricity, sustainability, and resilience, this study focused solely on workforce capabilities towards Industry 5.0 readiness, i.e. skills, upskilling, and workforce resilience. This focus is grounded in the understanding that human resources and skills form the foundation upon which Industry 5.0 maturity can develop. Skills enable organisations to adopt new technologies and pursue new directions towards a human-centric, sustainable, and resilient industry in a rapidly changing environment. By examining companies' capabilities with respect to the skills required for Industry 5.0 adoption, their upskilling initiatives, and their workforce resilience, this study provides insights into the importance of skills for industrial transformation and competitiveness. The aim of the cluster analysis was to identify distinct company profiles and understand their state and needs. To better interpret the results, company characteristics, such as size and type, were included in the analysis. We acknowledge that there are limitations in the statistical validation of the method as this study leverages a policy-driven instrument in an exploratory research study.

Using a tool developed collaboratively ensured that a wide range of perspectives was considered in the maturity assessment. Compared with survey-only data collection, conducting interviews ensured that misinterpretations were avoided and that concepts could be clarified with participants. Although the survey tool was developed based on other validated assessment frameworks and iteratively refined within the Industry 5.0 Community of Practice, its results should be used with care, recognising that they stem from a framework strongly influenced by policymaking. Additionally, clustering helps reveal typical company profiles, but doesn't reveal other characteristics that may underlie their performance. Lastly, this study intentionally focused on European industry, meaning that its results are also mainly relevant to European stakeholders. However, the conclusions are highly relevant to international stakeholders, as companies with these characteristics may exist elsewhere in the world.

5.4. Directions for future research

Every cluster presents unique challenges and more differentiated support is needed. "Ad hoc" risk falling behind if they don't transform their organisational inertia and work on their culture. Structured must build resilience to maintain and leverage their transformation momentum. Adaptive organisations face the challenge of maintaining their agility while also building resilience. Across all three clusters, the findings support the European Commission's argument that technologies must be complemented by human-centric practices, lifelong learning, and resilience (Breque et al., 2021). The clusters indicate that the transformation towards Industry 5.0 is significantly influenced by company culture, structure, and size.

Although K-means clustering was selected for this study, alternative clustering techniques will be investigated for future research. The present study prioritised transparency and ease of interpretation. However, in the future, the work could be extended by using other clustering methods, such as hierarchical clustering.

In the future, more empirical data should be collected to increase the coverage across industries, company sizes, and countries. The results could inform the design of managerial practices for skill management across companies with varying characteristics, as well as the implementation of incentives and support systems that meet these companies' needs. Additionally, the Industry 5.0 Learning and Assessment tool should be further developed to incorporate a feedback function, ultimately providing companies with an automated assessment result that highlights key areas for improvement.

6. Conclusions

The application of the tool and data analysis in this paper supports a valuable clustering analysis that advances understanding of workforce capabilities required for successful Industry 5.0 adoption. This study contributes to literature on Industry 5.0 by providing one of the first empirical typologies of workforce readiness. By moving beyond single-variable analysis to a configuration of variables, we demonstrate that workforce readiness manifests in three profiles or main clusters: "Ad hoc", "Structured", and "Adaptive", thus addressing research question 1. This approach challenges the assumption that larger firms are inherently more "ready" while highlighting that companies need both formal learning structures and mechanisms for adapting to industrial transformation.

In relation to RQ3, which examines the implications of different workforce readiness profiles for Industry 5.0 transformation, the proposed typology provides a structured basis for action. Rather than prescribing uniform solutions, the findings indicate that organisations require differentiated pathways depending on their capability configurations. Overall, the transition to Industry 5.0 requires not only the development of new skills, such as AI literacy, but also the alignment and integration of skills, learning systems, and resilience into coherent organisational configurations.

From a policy perspective, our findings suggest that generic upskilling incentives may not be the most efficient way. For "Ad hoc" firms, policy should focus on grants and incentives that support the establishment of learning infrastructures. For "Adaptive" firms, support should focus on providing access to digital learning platforms that enable their workforce to learn without incurring high costs. For "Structured" firms, incentives should be connected to the firm's transformation targets, such as sustainability KPIs and workforce retention metrics, rather than just training hours.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work, the authors used Claude for language correction, proofreading, and readability enhancement. The authors reviewed and edited the output as needed and take full responsibility for the content of the published article.

CRediT authorship contribution statement

Greta Braun: Writing – review & editing, Writing – original draft, Visualization, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Johan Stahre:** Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

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Appendix

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Table 6
Appendix with all questions from Learning and Assessment tool with pillar, theme, and inclusion.

Q#	Question	Pillar	Theme	Included in cluster analysis
	a) Do we have a common vision/purpose that motivates employees? (Purpose: the common goal – meaningful and strategic purpose combined with sustainable thinking – that goes beyond only making a profit towards which all stakeholders in the organisation strive and guides the organisation's strategies, policies, operations, and initiatives)	Human-centricity	Vision, Purpose	No
	b) Do we have a diversified and inclusive workforce (Diversified workforce in terms of gender, age, nationality, ethnicity, impairments, socio-economic backgrounds etc. Inclusive workforce in terms of fostering an atmosphere where everyone can contribute their unique skills and perspectives without facing discrimination or exclusion)?	Human-centricity	Diversity, Inclusion	No
Q3	c) Do we have skilled/knowledgeable workforce? 1. Digital literacy as a holistic skill to interact with, understand, enable, and even develop new digital manufacturing systems, technologies, applications, and tools	Human-centricity	Skills, Digital literacy	**Yes**
Q4	2. AI literacy as ability to use new AI and data analytics solutions while critically interpreting results	Human-centricity	Skills, AI literacy	**Yes**
Q5	3. Creative problem solving in times of abundant data and technological opportunities in smart manufacturing systems	Human-centricity	Skills, Creativity, Problem-solving	**Yes**
Q6	4. A strong entrepreneurial mindset including proactiveness and the ability to think outside the box	Human-centricity	Skills, entrepreneurial mindset	**Yes**
Q7	5. Ability to work physically and psychologically safely and effectively with new technologies	Human-centricity	Skills, Physical and psychological safety	**Yes**
Q8	6. Inter-cultural and inter-disciplinary inclusive, and diversity oriented mindset to address new challenges arising from a more diverse workforce	Human-centricity	Skills, Inclusive and diversity-oriented mindset	**Yes**
Q9	7. Cybersecurity, privacy, and data/information mindfulness to reflect the rapidly increasing digital footprint of respective value chain	Human-centricity	Skills, Cybersecurity	**Yes**
Q10	8. Ability to handle increasing complexity of multiple requirements and simultaneous tasks	Human-centricity	Skills, Handling complexity	**Yes**
Q11	9. Effective communication skills with humans, IT, and AI systems through different platforms and technologies	Human-centricity	Skills, Communication with humans and IT systems	**Yes**
Q12	10. Open-mindedness towards constant change, and transformation skills that constantly question the status quo and initiate knowledge transfer from other domains	Human-centricity	Skills, Open-mindedness	**Yes**
	d) Do we have innovative technologies with potential to enable human-centricity in work-related context? 1. Computation: technologies supporting the interplay with multimodal communication for seamless interaction (natural language processing, affective computing for experience optimisation etc.)	Human-centricity	Technologies for human-centricity, multimodal communication	No
	2. AI and machine learning: technologies facilitating the implication of big data and AI for data driven experience optimisation and improved analytical capabilities (human intention and support need recognition, user modelling for behaviour prediction etc.)	Human-centricity	Technologies for human-centricity, AI and machine learning	No
	3. Simulation and immersion: technologies facilitating remote presence and creating new capabilities for operating, maintaining, training, guidance and co-design of workplaces (Digital Twin for real-time data integration and synchronisation, Human Digital Twin, Extended Reality etc.)	Human-centricity	Technologies for human-centricity, simulation and immersion	No
	4. Robotics: technologies supporting the interplay of machine and workforce for an improved physical and psychological safety in collaborative task performance (robot learning by demonstration, learning by interaction, Intuitive robot programming)	Human-centricity	Technologies for human-centricity, robotics	No
	5. Industrial wearables and smart artefacts: technologies increasing individual competences and usability of manufacturing equipment, giving feedback on well-being and achievements, leading to higher work satisfaction and well-being of workforce (Exoskeleton for physical support, smart glasses for remote assistance, smart gloves for enhanced interaction etc.)	Human-centricity	Technologies for human-centricity, wearables and smart artefacts	No
Q18	6. Knowledge management: technologies supporting the contextual training, skill development and personal development of workforce (data visualisation for decision support, process visualisation for compliance/motivation/understanding)	Human-centricity	Technologies for human-centricity, knowledge management	**Yes**
	7. User interface: technologies supporting new forms of human machine interaction by providing real-time feedback on personal performance and holistic intuitive workplace interfaces (multimodal HMI for seamless interaction, situation aware assistance systems, adaptive dialogue/conversational systems etc.)	Human-centricity	Technologies for human-centricity, user interface	No
	8. Connectivity: technologies upskilling and motivating workforce, making skills and qualifications more visible, and facilitating knowledge sharing for a learning organisation (Internet of Everything IOE etc.)	Human-centricity	Technologies for human-centricity, connectivity	No
	9. Personalised systems: technologies designed in accordance with user expectations offering the labels and links a user of a given profile will use (real time feedback on personal performance, adaptive interaction technologies etc.)	Human-centricity	Technologies for human-centricity, personalised systems	No
	10. Miscellaneous HC enabling technologies: 6G and beyond, additive manufacturing, cloud/edge computing, blockchain etc.)	Human-centricity	Technologies for human-centricity, miscellaneous enabling tech	No

(*continued on next page*)

Table 6 (*continued*)

Q#	Question	Pillar	Theme	Included in cluster analysis
	e) Do we have in place infrastructure for persons with impairment?	Human-centricity	Accessibility	No
Q24	a) Do we have a learning organisation model? 1. Preservation of the cognitive dimension of work and autonomy in cognitive tasks	Human-centricity	Learning organisation, cognitive autonomy	**Yes**
	2. We apply supportive supervisory style and trust-based management	Human-centricity	Learning organisation, supportive supervision	No
Q26	3. We invest in trainings and upskilling/reskilling programs for employees to support their professional growth and advance their careers	Human-centricity	Learning organisation, training investment	**Yes**
	4. We support direct participation and workforce empowerment	Human-centricity	Learning organisation, participation and empowerment	No
	5. We support experimentations and new ways of working in our organisation	Human-centricity	Learning organisation, experimentation	No
	6. We apply system thinking to understand how different parts of the organisation interact and affect each other (system thinking is an approach that recognizes an organization as a complex system composed of interconnected elements and relationships)	Human-centricity	Learning organisation, systems thinking	No
	b) Do we ensure well-being? 1. We provide a variety of health and well-being programs for employees (health screenings, stress management programs, employee assistance program, fitness programs etc.)	Human-centricity	Well-being, health programmes	No
	2. We provide people-focused flexible working arrangements (teleworking, voluntary part-time working etc.)	Human-centricity	Well-being, flexible working arrangements	No
	3. We recognise and reward the hard work and achievements of employees via targeted measures such as promotions, bonuses, individual recognition (e.g. own-name patent registration) and other incentives	Human-centricity	Well-being, recognition and rewards	No
	4. We support workforce engagement via creating a positive work environment and encouraging open communication	Human-centricity	Well-being, workforce engagement	No
	c) Do we apply human-centric and purpose-driven approaches in design and deployment of technologies 1. Innovative technologies with potential to enable human-centricity enhancing the quality of workforce life, stimulating creativity and workforce interaction	Human-centricity	Human-centric technology design, quality of life	No
	2. We apply concrete technologies as a result of co-decision process	Human-centricity	Human-centric technology design, co-decision process	No
	*Questions 3–6 are only relevant for companies/organisations who design new technologies as their key activity 3. Human needs and experiences are at the centre of the HCT design process	Human-centricity	Human-centric technology design, human needs at centre	No
	4. The HCT design is an outcome of a co-creative process with stakeholders	Human-centricity	Human-centric technology design, co-creative process	No
	5. Multidisciplinary design teams (could include art, design, social scientists, culture and creativity experts etc.)	Human-centricity	Human-centric technology design, multidisciplinary teams	No
	6. HCT design process is in full compliance with ethical rules	Human-centricity	Human-centric technology design, ethical compliance	No
	d) Do we have impactful customer and community relations? 1. We listen to our customers' experiences in an open way as part of the constant learning and improvement process	Human-centricity	Customer & community relations, listening to customers	No
	2. We engage with our customers via different channels (social media etc.) to intensify our relationships and foster engagement	Human-centricity	Customer & community relations, multi-channel engagement	No
	3. We support local neighboring communities by participating in local events, sponsoring local organisations, collaborating with local suppliers and/or contributing to local charities etc.	Human-centricity	Customer & community relations, local community support	No
	4. We communicate openly and transparently with our customers and local neighboring communities	Human-centricity	Customer & community relations, transparent communication	No
	5. We empower our employees to actively build relationships with customers and local communities (encouraging them to participate in networking/local communities activities, rewarding employees' active engagement etc.)	Human-centricity	Customer & community relations, employee-led engagement	No
	a) Are we *ESG (Environmental, Social and Corporate Governance) compatible in social dimension? *ESG criteria are a set of environmental, social, and governance factors that are used to evaluate the sustainability and ethical impact of a company or investment. These criteria are employed to assess the non-financial performance of an organization and provide insights into its overall sustainability practices. For social dimension the ESG criteria evaluate a company's impact on society, including its treatment of employees, customers, suppliers, communities, and other stakeholders.	Human-centricity	ESG social dimension	No
	b) Do we have happy, motivated and satisfied employees in our organisation?	Human-centricity	Employee happiness, motivation, satisfaction	No
	c) Does the productivity and performance in our organisation have an improving trend?	Human-centricity	Productivity and performance trend	No
Q47	d) Do we have reduced staff turnover and improved retention in our organisation?	Human-centricity	Staff turnover and retention	**Yes**
Q48	e) Are we able to attract top talents in our organisation?	Human-centricity	Attracting top talent	**Yes**
	f) Do we have innovative technologies with potential to enable human-centricity in work-related context?	Human-centricity	Human-centric technology adoption (outcome)	No
	g) Do we generate positive social impact on local communities?	Human-centricity	Positive social impact on local communities	No
	h) Do we have positive organisation/brand reputation?	Human-centricity	Brand/organisation reputation (social)	No
	a) Do we have an environmental strategy in our company (such as climate change mitigation actions to ensure that a company business model is aligned with transition to a	Sustainability	Environmental strategy	No

(*continued on next page*)

Table 6 (*continued*)

Q#	Question	Pillar	Theme	Included in cluster analysis
	sustainable economy, environmental and energy management system and compliance with respective ISO standards etc.)?			
	b) Do we use renewable input energy sources derived from naturally replenishing or virtually inexhaustible resources and innovative green technologies (such as solar photovoltaic, battery/storage, heat pumps, electrolysers, carbon capture, grid, sustainable biogas/biomethane technologies as identified by the Net Zero Industry Act)?	Sustainability	Renewable input energy	No
	c) Do we use repurposed-reused-recycled input materials in our organisation designed/ labelled in compliance with the EU Eco-design Directive/Eco-design for Sustainable Products Regulation (ESPR)(more sustainable, circular and energy-performing design)?	Sustainability	Recycled/repurposed input materials	No
	d) Do we use ethical sourcing practices to ensure that the company/organisation's supply chain operates in a way that minimizes negative impact on people, communities and environment?	Sustainability	Ethical sourcing	No
	e) Do we use inputs non-hazardous to people and environment (compatible with REACH Regulation)?	Sustainability	Non-hazardous inputs (REACH)	No
	f) Are we located in nearly zero energy buildings (these buildings target a very low energy demand and require that the remaining energy needs are met by renewable sources. NZEB is a broader concept that encompasses both, energy-efficient buildings and passive buildings)?	Sustainability	Nearly zero energy buildings	No
	a) Are our production processes sustainable/regenerative? 1. Inputs are processed in a sustainable way (regenerative management of natural resources, green agricultural practices etc.)	Sustainability	Sustainable/regenerative production, inputs	No
	2. We optimise the use of energy in our organisation	Sustainability	Sustainable/regenerative production, energy optimisation	No
	3. We use eco-friendly packaging (biodegradable plastics, paper, reusable containers etc.)	Sustainability	Sustainable/regenerative production, eco-friendly packaging	No
	4. We apply water conservation methods during production process (closed-loop systems recirculating water within the production facility, technologies that reduce water consumption, rainwater harvesting/collecting systems for non-potable uses such as cooling or irrigation etc.)	Sustainability	Sustainable/regenerative production, water conservation	No
Q62	b) Do we provide targeted training schemes on sustainability/environmental impact for our management and employees?	Sustainability	Sustainability training	**Yes**
	c) Do we have green procurement policy in our organisation that favours products/ services respecting the environment?	Sustainability	Green procurement policy	No
	d) Do we have enviro-friendly transport/logistics processes (efficient and low-emission freight transport modes, green logistics practices)?	Sustainability	Environmentally-friendly transport/ logistics	No
	e) Do we analyse environmental impact of our activities/products/services? 1. We conduct a product life cycle assessment (LCA) – environmental impact throughout its life cycle from raw materials extraction to disposal	Sustainability	Environmental impact analysis, life cycle assessment	No
	2. We monitor our energy consumption to check the energy efficiency – we track energy use in buildings, transportation and manufacturing processes	Sustainability	Environmental impact analysis, energy monitoring	No
	3. We measure our Greenhouse gas (GHG) emissions	Sustainability	Environmental impact analysis, GHG emissions	No
	4. We calculate our water usage and waste we generate (manufacturing processes, office buildings etc.)	Sustainability	Environmental impact analysis, water and waste	No
	5. We develop and use environmental KPIs to track progress towards environmental targets	Sustainability	Environmental impact analysis, environmental KPIs	No
	f) Do we actively engage with local communities? 1. We collect data on the current environmental conditions and community needs in the area where our organisation/ company operates	Sustainability	Community engagement, environmental data collection	No
	2. We determine specific Key Performance Indicators (KPIs) that align with our company's environmental goals and are relevant to local communities (waste management, biodiversity preservation, local transport etc.)	Sustainability	Community engagement, local KPI alignment	No
	3. We engage with local communities (local administrations, local NGOs, environmental agencies) to gather their feedback and reflect it in our decision-making process	Sustainability	Community engagement, stakeholder engagement	No
	a) We are ESG compatible in environmental dimension (Environmental component of ESG focuses on evaluating a company's impact on the environment and its performance in managing environmental risks and opportunities. These criteria assess various aspects related to environmental sustainability such as GHG emissions, energy efficiency, renewable energy etc.)	Sustainability	ESG environmental dimension	No
	b) We are aligned with EU Taxonomy (the EU Taxonomy is a classification system establishing a list of environmentally sustainable economic activities, to facilitate sustainable investment)	Sustainability	EU Taxonomy alignment	No
	c) Do we produce negative emissions (including negative pollution) in our organisation?	Sustainability	Negative emissions	No
	d) Do we have green/Net Zero technologies in our organisation?	Sustainability	Green/Net Zero technologies	No
	e) Do we have positive impact on biodiversity and restoration of natural ecosystems?	Sustainability	Biodiversity impact	No
	f) Do we generate positive environmental impact on local communities?	Sustainability	Positive environmental impact on local communities	No
	g) Do we have positive organisation/brand reputation?	Sustainability	Brand/organisation reputation (environmental)	No
	a) Do we have diversified revenues? (ability to generate income from multiple sources)	Resilience	Diversified revenues	No
	b) Do we have flexible supply chains? (ability to respond to short-term changes in market demands)	Resilience	Flexible supply chains	No
	c) Do we have sustainable profit? (ability to generate consistent financial returns while simultaneously considering and managing environmental, social, and governance "ESG" factors)	Resilience	Sustainable profit	No

(*continued on next page*)

Table 6 (*continued*)

Q#	Question	Pillar	Theme	Included in cluster analysis
Q82	d) Do we have a critical skill redundancy in our organisation? (essential skills and knowledge are not solely concentrated in a single individual or a limited group of employees)	Resilience	Critical skill redundancy	**Yes**
	e) Do we have intellectual assets (patents, licences etc.)?	Resilience	Intellectual assets	No
	f) Do we have robust and scalable IT infrastructure (adaptive and flexible information technologies, robust hardware/software framework and supportive mechanisms enabling efficient and secure function of a company/organisation's information technology operations)?	Resilience	Robust and scalable IT infrastructure	No
	g) Do we have robust and scalable cybersecurity infrastructure (Comprehensive set of measures to protect a company/organization's digital assets, data, and systems (firewalls and network security, secure network architecture etc.)?	Resilience	Robust and scalable cybersecurity infrastructure	No
	a) Do we have effective measures and/or targeted strategy in place to ensure resilience of our organisation? 1. We perform regular foresight exercises and risk assessments of our organisation	Resilience	Resilience strategy, foresight and risk assessment	No
	2. We have contingency plan (business continuity strategy) to adapt to risk events	Resilience	Resilience strategy, contingency planning	No
	3. We develop and use KPIs related to risk management and financial performance	Resilience	Resilience strategy, risk management KPIs	No
	4. We perform regular resilience audits (on systems, processes and controls in our organisation) to identify areas for improvements	Resilience	Resilience strategy, resilience audits	No
	5. We perform regular stakeholders/customers feedback exercises to identify strengths and weaknesses of our organisation	Resilience	Resilience strategy, stakeholder feedback	No
	b) Do we have effective measures in place to ensure financial and corporate resilience of our organisation? 1. Financial indicators such as liquidity/solvency/profitability ratios and cash-flow patterns' analysis to assess different aspects of a company/organisation financial health and to ensure absorption of market shocks	Resilience	Financial resilience, financial health indicators	No
	2. We re-invest in low-risk and/or sustainable financial products (such as green bonds)	Resilience	Financial resilience, low-risk/ sustainable investment	No
	3. We have financial reserves on preventive measurements against anti-competitive behaviour, anti-trust and monopoly practices	Resilience	Financial resilience, reserves against anti-competitive risk	No
	c) Do we have effective policies and measures in place to mitigate the risk of supply chain disruptions in our organisation? 1. We have an adequate stockpile (sufficient amount of goods, raw materials, or components to ensure smooth production, timely order fulfilment, and the ability to respond to unexpected fluctuations in demand or supply)	Resilience	Supply chain resilience, stockpile	No
	2. We have diversified suppliers	Resilience	Supply chain resilience, diversified suppliers	No
	3. We perform a supplier risk assessment and create supplier risk profiles	Resilience	Supply chain resilience, supplier risk assessment	No
	d) Do we have in place an effective mix of policies, technical measures and employee education schemes to ensure an adequate level of cybersecurity in our organisation? 1. Our IT infrastructure is secured by the latest solutions and services	Resilience	Cybersecurity resilience, secured infrastructure	No
	2. Flexibility of IT infrastructure – in case of crisis we can replace our outsourced IT infrastructure immediately	Resilience	Cybersecurity resilience, IT flexibility	No
	3. We have in place an energy redundancy system (back-up electricity generators etc.)	Resilience	Cybersecurity resilience, energy redundancy	No
	4. We use encryption to protect sensitive data from unauthorised access	Resilience	Cybersecurity resilience, encryption	No
	5. We implement security monitoring and protocols to detect and quickly respond to security incidents	Resilience	Cybersecurity resilience, security monitoring	No
Q102	6. We perform regular cybersecurity trainings for our employees	Resilience	Cybersecurity resilience, employee training	**Yes**
	e) Do we have an adequate level of digital technology adoption and use in our organisation? 1. We perform online purchasing and e-commerce sale	Resilience	Digital resilience, e-commerce	No
	2. We have access to internet, fixed broadband access and mobile broadband connection	Resilience	Digital resilience, connectivity access	No
	3. We have a system for remote staff connection/work in case of emergency	Resilience	Digital resilience, remote work capability	No
Q106	4. We provide targeted trainings on digital skills to our employees	Resilience	Digital resilience, digital skills training	**Yes**
	5. We have an organisation website (home page), we use social networks and e-business technologies such as Enterprise Resource Planning software (ERP) or Customer Relationship Management software (CRM)	Resilience	Digital resilience, digital business tools	No
	6. We use high cloud computing services in our organisation such as accounting software applications, CRM software, computing power	Resilience	Digital resilience, cloud computing	No
	f) Do we invest in R&I and intellectual property to increase the organisation's resilience and adaptability to the market changes? 1. We provide resources for R&I and support experimentation in our organisation	Resilience	Innovation & IP resilience, R&I resources	No
	2. We develop new sustainable products/services	Resilience	Innovation & IP resilience, new sustainable products	No
	3. We monitor trends and keep ourselves updated on new technologies (both – on the market and in the pipeline)	Resilience	Innovation & IP resilience, trend monitoring	No
	4. We develop new intellectual assets (patents, trademarks, licences, copyrights etc.)	Resilience	Innovation & IP resilience, new IP development	No
	5. We build strategic partnerships with start-ups, universities, industries and other stakeholders to share knowledge, resources and experience	Resilience	Innovation & IP resilience, strategic partnerships	No
	a) Are we an adaptable and competitive organisation able to react quickly and recover from disruptions/uncertainties on the market?	Resilience	Adaptability and competitiveness	No

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Table 6 (*continued*)

Q#	Question	Pillar	Theme	Included in cluster analysis
	b) Is our organisation ESG compliant for financial and corporate governance component?	Resilience	ESG financial/governance compliance	No
	c) Do our products/services achieve top market positions?	Resilience	Top market position	No
	d) Do we have positive organisation/brand reputation?	Resilience	Brand/organisation reputation (resilience)	No

Data availability

Data will be made available on request.

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