SKILLS 4 CIRCULARITY

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Upskilling and reskilling the textile industry sector to face the challenges in recycling, traceability and certification of recycled products

Desk Research on Urgent Skills Gaps: Job Advertisements Analysis

Document Information

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Contents

Abbreviations and Acronyms

Abbreviation	**PIN: FONDAZIONE PIN - POLO DI PRATO UNIVERSITA DI FIRENZE** **UPC: UNIVERSITAT POLITÈCNIACA DE CATALUNYA**
Acronym	**LLM**: LARGE LANGUAGE MODEL **ESCO**: EUROPEAN SKILLS, COMPETENCES, QUALIFICATIONS AND OCCUPATIONS
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Labour Market Analysis and Identification of Urgent Skills

Context and Role

Within Task 1.1 *"Rapid Needs Assessment of Urgent Skills Gaps"*, PIN, with the support of UPC, acted as responsible partner for the desk research activities aimed at identifying urgent and emerging skills demanded by the labour market.

The activity was carried out in coordination with the project partners and under the general framework defined by the project coordinator, contributing directly to the evidence base for subsequent surveys, interviews, and training design activities.

Objectives of the Desk Research

The main objective of the desk research was to collect signals derived from online job advertisements, with the perspective of analysing and interpreting labour market demand in the subsequent phases of the project, starting precisely from the results of this first analysis.
The objectives of the activity were to:

- identify skills currently demanded by employers in relation to circularity, sustainability, and innovation in the textile sector;
- detect urgent skills gaps, understood as skills for which demand is already observable in the labour market but not yet sufficiently addressed by existing training and qualification systems;
- provide a market-driven empirical basis to inform the qualitative research phases of the project (focus groups, surveys, interviews).

Analytical Focus: From Job Demand to Skills Demand

The analysis was grounded in the assumption that job advertisements represent a direct and timely proxy of employers' skill needs. Rather than relying exclusively on theoretical or policy-driven definitions of emerging skills, the desk research aimed to observe what companies are actually asking for when recruiting staff.

Special attention was paid to the following aspects within job postings:

- required technical competences related to sustainable materials, recycling processes, quality control, and production optimisation;
- transversal skills increasingly associated with innovation and sustainability (e.g. digital competences, problem-solving, process monitoring);
- references to environmental standards, circular economy principles, and sustainability-oriented practices.

This approach allowed to identify skills that are both urgent and innovation-oriented, thus aligning with the project's strategic focus on supporting the green and digital transition of the textile sector.

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Relevance for Subsequent Project Activities

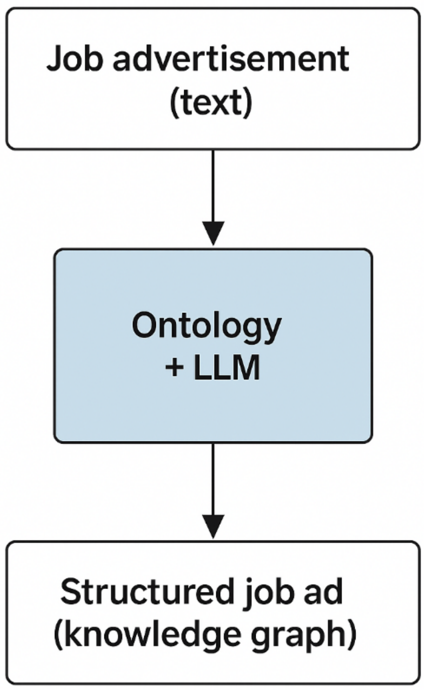
The results of the desk research constitute a foundational input for the next phases of the project. In particular, they:

- support the design of surveys and interviews by grounding them in empirically observed skills demand;
- provide a structured basis for discussion within focus groups with stakeholders and companies;
- contribute to the identification of priority skill areas to be addressed in the development of training contents and curricula.

The desk research therefore plays a strategic role in ensuring that the project's outputs respond to actual labour market needs, enhancing the relevance and impact of the Skills4Circularity project.

Methodology Adopted to Extract Skills from Online Job Advertisements

To move from destructured job advertisements (copied from online sources) to a structured and comparable set of skills, it was applied a methodology which integrates Semantic Web principles (ontologies and knowledge graphs) with Large Language Models (LLMs), with the aim of reducing semantic ambiguity and enabling systematic coding and aggregation.



RATIONALE: WHY AN ONTOLOGY + LLM PIPELINE IS NEEDED

Job ads are information-rich but inherently unstructured. The adopted approach treats each job ad as a text source to be converted into a *knowledge graph*, using ontologies as a conceptual “schema” that constrains interpretation and supports consistent extraction of entities, attributes and relations (e.g., skills required, job title, contract type).

In practical terms, ontologies provide the domain concepts to be detected in text, while LLMs—guided by prompt engineering—perform the mapping from text fragments to those concepts.

A skills-recognition approach based solely on *simple textual analysis or keyword matching is not sufficient* to reliably identify skills from job advertisements, because it fails to capture the context in which a skill is mentioned.

Job ads do not list skills in isolation: skills acquire their meaning from the occupational role, production context, and organisational setting in which they are embedded. Two skills with the same or very similar wording may represent substantially different professional realities when applied in different contexts.

For example:

- the skill *“quality control”* may refer to manual inspection of finished garments in a small-scale textile workshop, or to statistical process control and compliance with international standards in an industrial production environment;
- *“digital skills”* may indicate basic use of office software for documentation purposes, or advanced use of CAD systems, digital pattern-making tools, or production monitoring software;
- *“process optimisation”* may describe incremental improvements in sewing or finishing operations, or the redesign of entire production workflows using lean or sustainability-oriented approaches.

A purely textual or frequency-based approach would treat these occurrences as equivalent, thereby flattening important differences and producing misleading results. What is lost is precisely the information that is most relevant for training design: how a skill is applied, at what level of complexity, and within which production logic.

The ontology-based approach addresses this limitation by providing a conceptual framework that preserves context. Skills are not extracted as isolated words, but as elements connected to:

- a specific occupation,
- a set of tasks or responsibilities,
- and an organisational or production setting.

LLMs, when guided by ontologies, can interpret textual expressions in relation to these surrounding elements, enabling a context-aware extraction of skills. This is particularly important in sectors such as textiles, where the same terminology may cover highly heterogeneous practices depending on company size, technological intensity, and position along the value chain.

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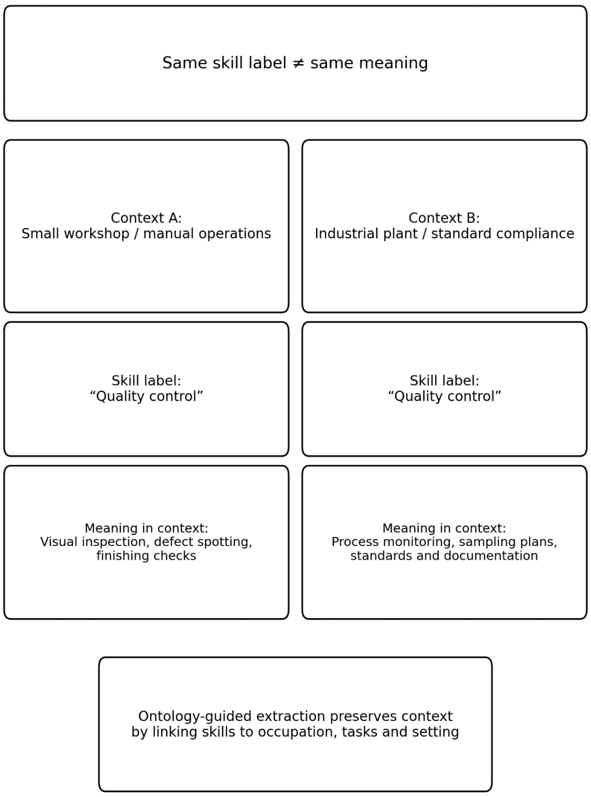
Figure 2. Why context matters in skills recognition



OVERVIEW OF THE PROTOCOL (AS IMPLEMENTED)

The workflow follows the “Job Ads Processing Protocol” as a two-step structuring and coding process.

Step 1 — Structuring Job Ads Using a Job-Ad Ontology (First Knowledge Graph)

- *Ontology development / selection*: a general job-ad ontology is used to define the expected structure of a job advertisement (e.g., job title, job description, job type, offered-by/company attributes, required skills).
- *LLM conceptual grounding*: the LLM is instructed to apply the ontology concepts when reading the unstructured job-ad text.
- *Prompt engineering and concept identification*: the LLM processes the original job ad and extracts all relevant fields and relations expressed in the ontology (notably the *hasRequiredSkill* relation).
- *Structured output*: the model returns a structured representation that can be interpreted as a subgraph of a knowledge graph, connecting the job ad to job characteristics and a list of required skills.

Step 2 — Alignment to ESCO (Second Knowledge Graph; Standardised Coding)

Because the first structured output is still expressed in non-standard concepts, a second step aligns the extracted skills to the ESCO framework to enable comparability and aggregation.

- advanced grounding of the LLM on the ESCO ontology;

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- similarity-based matching between extracted skills and ESCO concepts;
- generation of ESCO preferred labels, alternative labels, concept URIs, and related metadata.

What we get:

The dataset summarises the skills extracted from the job advertisements collected by partners and the subsequent standardisation of those skills into ESCO. In practice, each record represents the outcome of a structured pipeline:

1. partners select relevant job advertisements and paste the full text into a shared Excel template;
2. texts are elaborated in their original language;
3. skills are extracted through ontology-driven analysis (non-ESCO) and presented in english;
4. extracted skills are mapped to ESCO, producing a standardised representation.

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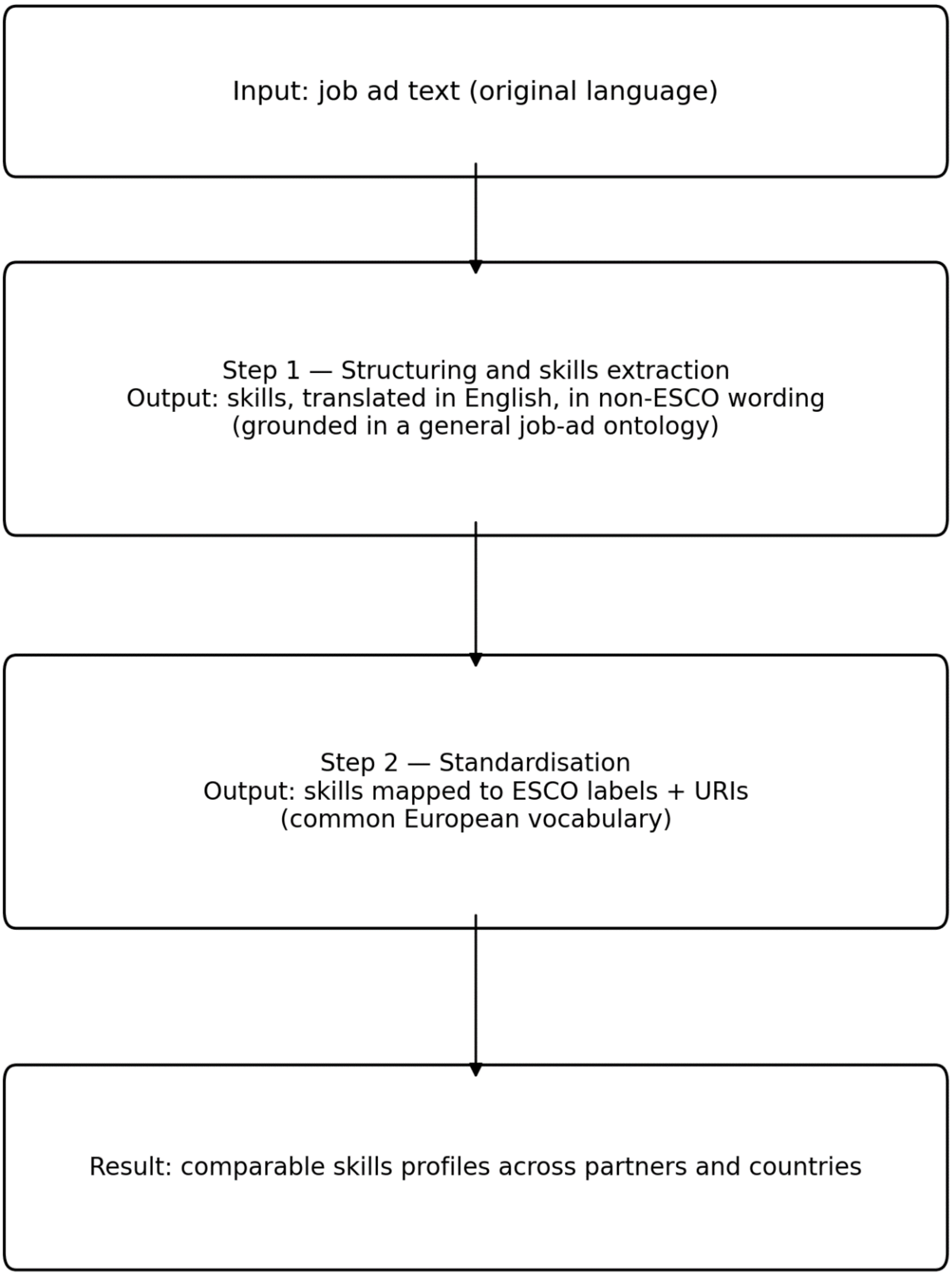
Figure 3. Two-step pipeline: extraction and ESCO alignment



As a result, each job advertisement is associated with multiple skills, spanning technical, organisational, and quality-related dimensions.

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Because the first structured output is still expressed in non-standard concepts, a second step is used to align extracted skills to an official standard—ESCO—to enable comparability and downstream aggregation.

1. Advanced training with standard ontology: a second LLM stage is configured with an ontology of standard concepts (ESCO).
2. Similarity/matching procedure: the LLM is prompted with the extracted (non-standard) structured skills and tasked to identify the closest ESCO nodes, producing for each skill:
   - ESCO preferred label,
   - alternative labels,
   - concept URI,
   - concept type and other standard metadata (e.g., reuse level, status).
3. Standardised output: the result is a second structured dataset that can be seen as a second knowledge graph, where extracted skills are anchored to ESCO identifiers (conceptUri), enabling consistent reporting and later integration with other datasets or qualifications frameworks.

WHAT THIS ENABLES FOR TASK 1.1

Applying this protocol supports Task 1.1 in three concrete ways:

- *Traceability**:*** each extracted skill remains linked to the original job-ad text through the intermediate structured representation, supporting auditability and qualitative review.
- *Comparability* across countries/languages: once aligned to ESCO, results can be compared across partner countries even when job ads were originally collected in different languages.
- *Scalability and versatility*: the same pipeline can, in principle, encode job ads against additional standards or repositories (beyond ESCO) by switching the “standard ontology” layer.

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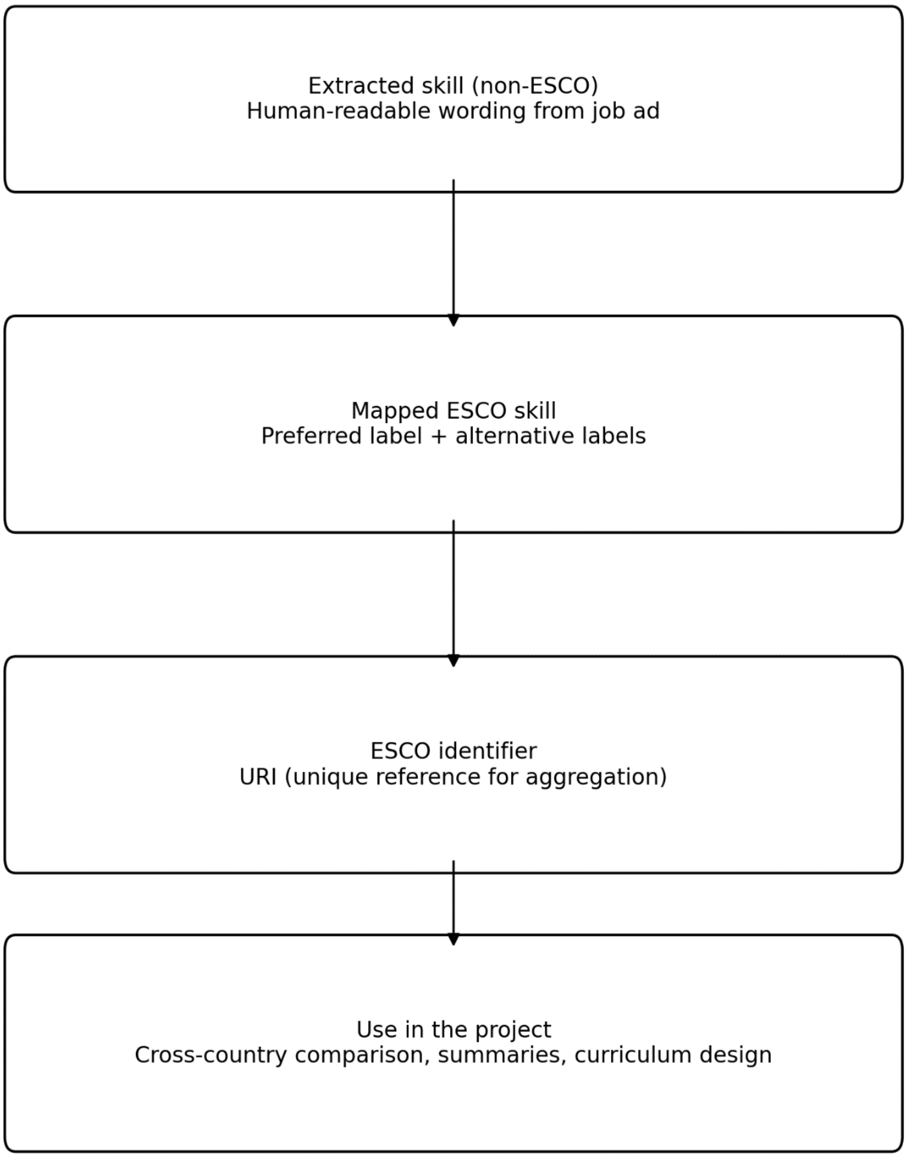
Figure 4. ESCO-aligned outputs for reporting and aggregation



Methodological Adjustment: From Automated Scraping to Partner-Based Manual Data Collection

During the initial phase of Task 1.1, the project consortium explored the feasibility of an *automated web scraping approach* to collect job advertisements from international and national online job boards. A first proof-of-concept was presented, based on scraping activities conducted on selected international platforms and using predefined keywords related to the textile sector, recycling, and sustainable production.

This preliminary exercise proved valuable in testing the technical viability of large-scale data collection and in highlighting the richness of job-ad data for skills analysis. At the same time, it allowed the consortium to identify a series of *critical methodological, technical, legal, and analytical issues,* which led to a reasoned decision to *adopt a manual, partner-based scraping strategy* for the main data collection phase.

Technical and Legal Constraints of Automated Scraping

A first major limitation concerns the increasing diffusion of anti-scraping systems implemented by job-posting platforms. These measures are often explicitly designed to prevent automated data extraction, in particular to protect content from large-scale reuse and from training processes related to artificial intelligence.

Although the research team involved in the project has the technical expertise to bypass such protections, this possibility raised important ethical and legal considerations within the consortium. The group considered it essential to avoid approaches that could place the project in a legally ambiguous position or conflict with the ethical standards expected in an Erasmus+ project. The example shown during the internal discussion was considered acceptable only because the data were used exclusively for aggregated analysis and for methodological testing, but it could not be generalised as a standard operational solution.

Statistical and Analytical Considerations

Beyond technical issues, the consortium engaged in a broader reflection on the statistical and economic meaning of the data produced through automated scraping.

Keyword-based scraping was recognised as predominantly *confirmatory* in nature: it efficiently measures the presence of predefined skills in the labour market, but it may limit the ability to detect unexpected or emerging competences outside the initial keyword set. At the same time, this confirmatory character was also identified as a strength, since many projects hypothesised emerging skills without verifying whether these are actually demanded by employers. Job-ad analysis makes it possible to empirically assess this demand.

A persistent challenge, however, concerns the identification of job ads genuinely belonging to textile companies. Given the cross-sectoral nature of occupations and the graph-like structure of contemporary labour markets, job titles alone do not allow a reliable sectoral attribution. In practice, the only element that can provide such information is the textual description of the job ad itself, which often requires contextual and linguistic interpretation.

Rationale for Partner-Based Manual Scraping

In light of these considerations, the consortium agreed that a manual, partner-based scraping approach would better serve the objectives of Task 1.1.

Each partner, drawing on its local domain knowledge, is better positioned to:

- identify the most relevant national job portals;
- interpret job descriptions in the original language;
- assess whether a job ad is plausibly linked to the textile sector, based on contextual cues in the text.

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This approach significantly improves the relevance and validity of the collected data, while avoiding the legal and ethical risks associated with automated scraping.

Operational Implications and Added Value

To ensure harmonisation across countries, PIN provided all partners with:

- *standardised Excel templates* for reporting job advertisements;
- a *shared set of keywords* to guide the initial search process;
- clear instructions on how to copy and paste job ads in full, preserving the original textual content.

This decentralised but coordinated method combines local expertise with centralised processing and analysis, enabling PIN to subsequently translate, structure, and extract skills using the ontology- and LLM-based methodology described in the previous section.

Moreover, collecting job ads manually allows the consortium to capture cross-sectoral signals, highlighting how skills relevant to textile circularity may emerge in more innovative or adjacent sectors. These insights are particularly valuable as inputs for the project's focus groups and survey activities.

Methodological Coherence with Project Objectives

The decision to move from automated scraping to partner-based manual data collection was therefore not a fall-back solution, but a methodologically grounded choice. It ensures:

- compliance with legal and ethical standards;
- better alignment with project timelines;
- higher analytical quality of the data;
- stronger integration between quantitative job-ad analysis and qualitative research activities.

This methodological adjustment strengthens the overall robustness of Task 1.1 and enhances the capacity of the project to identify urgent and innovation-driven skills grounded in real labour market demand.

Alignment with CEDEFOP Short-Term Skills Anticipation (STAS)

The methodological approach adopted in Task 1.1 is strongly aligned with the analytical logic promoted by CEDEFOP, in particular with the Short-Term Anticipation of Skills trends and VET demand (STAS) tool, which combines labour market intelligence sources to monitor evolving skill needs and inform education and training policies. Both approaches share the underlying assumption that timely signals from the labour market—especially those derived from job advertisements—constitute a valuable proxy for emerging and urgent skills demand, complementing more structural and medium-term forecasting instruments.

In terms of continuity, the project approach converges with STAS in several key aspects. First, both rely on online job advertisements as a core empirical source to capture short-term dynamics in skills demand. Second, both recognise the importance of standardisation and classification to ensure comparability and usability of results across contexts. In this respect, the project's systematic alignment of extracted skills with the ESCO framework mirrors CEDEFOP's emphasis on using common European taxonomies to support aggregation, comparison, and policy relevance. Finally, both approaches are conceived as complementary to qualitative instruments (such as surveys, interviews, and stakeholder consultations), rather than as stand-alone tools.

At the same time, the approach developed within this project introduces elements of methodological advancement with respect to existing STAS-based analyses. In particular, the ontology-driven and LLM-supported pipeline allows for a context-aware interpretation of job advertisements, going beyond keyword-based or purely statistical text analysis. By explicitly modelling the relationships between occupations, tasks, skills, and organisational settings, the method reduces semantic ambiguity and captures differences in skill meaning that depend on production context, technological intensity, or position within the value chain. This is especially relevant in cross-sectoral domains such as sustainable textile production and circular economy, where identical skill labels may correspond to substantially different professional practices. In this sense, the project contributes to refining the qualitative depth of short-term skills intelligence, while remaining compatible with CEDEFOP's standardisation principles.

Another point of advancement lies in the decentralised data collection strategy, which leverages partners' domain knowledge to select relevant job advertisements at national level before applying a centralised, standardised extraction and coding process. This hybrid model mitigates some of the known limitations of fully automated scraping and enhances the interpretability of results, particularly for niche sectors and emerging occupational profiles that may be underrepresented or poorly classified in large-scale datasets.

At the same time, the project explicitly acknowledges its limitations, in line with CEDEFOP's cautious use of online vacancy data. The results are sensitive to the coverage and representativeness of online job postings, which vary across countries, firm sizes, and occupational segments. Moreover, despite the use of ontologies and ESCO alignment, the extraction and mapping process remains subject to interpretative uncertainty, especially for transversal or hybrid skills. Finally, the approach is designed to capture short-term and innovation-driven signals, and therefore does not aim to replace medium- or long-term forecasting tools, but rather to complement them.

Overall, the methodology proposed in Task 1.1 can be seen as fully consistent with CEDEFOP's STAS framework, while offering a focused experimental contribution that explores how ontology-based and AI-assisted techniques can enhance the granularity, precision, contextualisation, and policy relevance of short-term skills anticipation in specific sectors.

Why original-language graph construction is methodologically preferable to "translate-first"

In this project, job advertisements are first transformed into a structured representation (the first knowledge graph) **in their original language**, and only afterwards are the extracted skill labels translated into English for harmonisation and ESCO mapping. This sequence is methodologically preferable to the alternative workflow—translating the full job-ad text first and then constructing the graph—because it preserves the linguistic and contextual integrity of the source data at the moment where meaning is interpreted and relationships are established.

Preserving meaning before standardising language

A job advertisement is not a neutral list of terms: it is a short, context-rich document in which meaning is conveyed through domain-specific wording, idioms, implicit assumptions, and culturally embedded references to roles, seniority, and work practices. When the full text is translated before any semantic structuring takes place, two types of distortion can occur:

1. **Lexical distortion**: different words in the original language may collapse into the same English term, or a single term may be translated in multiple ways depending on context. This can artificially inflate or reduce the presence of certain skills and blur distinctions that matter in practice.

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2. **Contextual distortion**: the meaning of a skill often depends on the surrounding text—tasks, responsibilities, tools, and production setting. Translation can unintentionally alter nuance (e.g., whether a requirement implies operational execution, supervision, or design responsibility), which then affects how an ontology-based extraction interprets the role–task–skill relationships.

By contrast, constructing the first knowledge graph in the original language ensures that semantic interpretation—i.e., identifying entities, linking skills to tasks, and situating them within an occupational context—happens **before** any linguistic normalisation. In other words, the workflow separates two different objectives:

- **understanding** the job ad (semantic structuring), and
- **comparing** results across countries (translation and ESCO alignment).

This separation reduces the risk that translation choices drive the analytical outcome.

Avoiding the “translation as a hidden modelling decision”

When translation happens first, the translator (human or machine) effectively becomes an unacknowledged part of the modelling pipeline. Translation is not only a technical step; it is also an interpretative step, because it requires selecting one meaning among alternatives. If this interpretative layer precedes the ontology-based structuring, then the resulting graph can reflect translation artefacts rather than the employer’s original intent.

Processing in the original language makes translation more controlled and transparent, because translation is applied **only to the extracted skill labels** after they have been identified in context. This greatly reduces the amount of text that must be translated and limits the translation step to a clear function: harmonising labels for standardisation and ESCO mapping.

Better traceability and auditability

The project aims to maintain traceability from skills back to job advertisements. Building the first graph in the original language supports auditability because it preserves a clear link between:

- the exact expression used by the employer,
- the tasks and responsibilities in the ad,
- and the extracted skill.

If translation is applied to the full text first, it becomes harder to verify whether a given ESCO-mapped skill genuinely reflects the original requirement or is partly an effect of how the translation rendered the passage. Original-language structuring therefore strengthens transparency and makes quality assurance more robust.

Why this choice enables an evolutionary path and broader monitoring across cultural contexts

Beyond immediate methodological robustness, the original-language-first workflow provides a clear **evolutionary pathway** for scaling and adapting the tool to diverse labour market and cultural environments—especially those that are typically less represented in large-scale scraping-based analyses.

Making the tool adaptable to linguistic diversity

Many established web-scraping analyses implicitly privilege languages and labour markets where:

- job boards have high standardisation,

- ads follow predictable templates,
- and a large amount of data is already available in English or easily translatable.

However, important parts of the textile ecosystem—especially SMEs, local supply chains, or regional clusters—often publish job ads that are:

- shorter, more informal,
- less standardised,
- strongly context-dependent,
- and embedded in local terminology.

Processing job ads in the original language allows the methodology to be extended to these contexts without forcing them into an “English-first” logic. In practice, this means the tool can evolve toward a genuinely European (and potentially wider) monitoring instrument, rather than one constrained to the linguistic and structural patterns of the most digitised labour markets.

Supporting monitoring where scraping is weaker or biased

Even when scraping is technically feasible, it can systematically underrepresent certain contexts:

- countries where job ads are dispersed across many small platforms,
- sectors where recruitment happens through semi-formal channels,
- or regions where postings contain culturally specific role descriptions and skill references.

An original-language-first approach, combined with partner-based selection or targeted data collection, makes it possible to monitor skill signals in contexts that traditional scraping often misses. This is particularly relevant for circular textile value chains, where crucial roles may exist in smaller firms, repair/upcycling initiatives, or local logistics and sorting activities that do not appear prominently on major international job boards.

Enabling incremental improvements without redesigning the whole pipeline

This workflow also supports gradual tool development:

- The first-stage ontology and extraction logic can be improved language by language (or region by region), leveraging partner feedback and domain expertise.
- The translation and ESCO mapping step remains a stable harmonisation layer, enabling cross-country comparison even while the upstream extraction improves.
- New cultural contexts can be added without requiring the entire pipeline to be rebuilt; instead, the project can extend coverage by adding language-specific resources (domain terminology, examples, validation rules) while keeping a common European reporting layer through ESCO.

In short, the workflow provides a modular architecture: **local semantic interpretation first, European standardisation second**. This modularity is a key asset for evolving from a project-specific analysis to a monitoring approach that can operate reliably across different cultural and linguistic environments.

Why original-language processing enables monitoring of diverse labour-market contexts

An important implication of building the first knowledge graph in the original language of the job advertisement is that it enables the analysis of skill demand in labour-market contexts that are typically underrepresented in large-scale, keyword-based web scraping.

In many job advertisements—especially those published by SMEs, local production units, or actors involved in repair, reuse, sorting, and recycling activities—skills are not expressed through standardised or internationally recognisable labels. Instead, requirements are often articulated through **task-oriented and context-specific descriptions**, referring to concrete activities (e.g. handling production waste, selecting incoming materials, checking recovered items, maintaining basic traceability records, interacting with local suppliers or collectors) rather than abstract skill names.

If such job-ad texts were translated and standardised before any semantic structuring takes place, much of this contextual information would risk being flattened into generic terms (e.g. “waste”, “documentation”, “suppliers”), making it difficult to distinguish between different types of competences and to correctly associate them with circular-economy skill areas. In contrast, analysing the text in its original language allows the first knowledge graph to capture **the relationship between tasks, skills, and production context** as they are actually described by employers.

Only after this contextual interpretation is established are the extracted skills translated into English and mapped to ESCO concepts. This makes it possible to recognise, for example, that different local expressions referring to material selection, quality checks on recovered textiles, or batch tracking all correspond—once standardised—to ESCO skills related to waste management, textile sorting, traceability, or product data management.

As a result, the workflow supports the monitoring of skill demand in culturally and organisationally diverse settings, including those where job advertisements are shorter, less formalised, or linguistically distant from standard policy or labour-market terminology. This significantly broadens the analytical coverage of the tool and strengthens its capacity to inform training pathways that are relevant not only for highly standardised industrial contexts, but also for local and emerging segments of circular textile value chains.

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Scraping results: an example

The dataset summarises the skills extracted from the 313 job advertisements collected by partners (annexe I) and the subsequent standardisation of those skills into ESCO. In practice, each record should be read as the outcome of a short pipeline: (i) a partner selects a relevant job ad on national job boards and pastes the full text into the shared Excel template; (ii) the content is analysed using an ontology-driven approach to identify the skills explicitly or implicitly required by the employer (these first skills are not yet in ESCO); (iv) the extracted skills are then mapped to the closest ESCO skills, producing a second list that uses a common European vocabulary. As a result, each job advertisement is associated with multiple skills (often spanning technical, organisational, and quality-related aspects), and for most ads there is a corresponding ESCO-aligned version of the same information.

To make the results easy to interpret, below is an example based on the **first job advertisement (Spanish partner: TÈXTILS.CAT; ESCO occupation: "textile product developer")**.

Example (Job Ad #1 — Spain, TÈXTILS.CAT)

Job advertisement text (as collected)

Development & Industrialisation Technician (textile) — main responsibilities mentioned in the ad:

- Development of textile projects: preparation of design proposals and prototypes; pattern development and industrialisation of patterns
- Improvement of existing products
- Preparation of technical documentation for textile products
- Monitoring samples and prototypes through technical sheets
- Resolving quality and garment-manufacturing issues
- Technical training for the production plant
- Research and selection of new materials and accessories/components ("fornitures")

(Contract details and general conditions are also reported, such as permanent contract and salary commensurate with experience.)

Extracted skills (non-ESCO wording)

For this single advertisement, the extraction identifies a **set of distinct skills**, including:

- Development of prototypes
- Implement pattern making
- Ensure compliance with quality standards
- Guarantee customer satisfaction
- Ensure compliance with legal requirements
- Analyse production processes for improvement
- Ensure compliance with company regulations
- Define quality standards

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- Demonstrate reliability
- Monitor production developments
- Communicate about quality issues
- Compile quality documentation
- Manage quality of products
- Use manual sewing techniques
- Analyse test data
- Assist in the development of manufacturing instructions
- Develop manufacturing policies
- Check manufacturing instructions

ESCO skills (standardised)

The same skills are then translated into ESCO-compatible labels, for example:

- Develop prototypes
- Create patterns for textile products
- Apply quality standards
- Ensure customer focus
- Ensure compliance with legal requirements
- Analyse production processes for improvement
- Ensure compliance with company regulations
- Define quality standards
- Demonstrate reliability
- Monitor developments in field of expertise
- Communicate about quality issues
- Compile quality documentation
- Manage quality of products
- Use manual sewing techniques
- Analyse test data
- Assist in developing manufacturing instructions
- Develop manufacturing policies
- Apply manufacturing instructions

This example shows how the results should be read throughout the dataset: for each job ad, a "raw" list of skills is first produced in plain language, closely reflecting the wording and meaning found in the ad; then a second list provides the ESCO-aligned equivalents, enabling comparison and aggregation across partners and countries.

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Project-relevant skills by conceptual area (Non-ESCO extraction and ESCO alignment)

The information obtained from the scraping and classification activities described above is presented and summarised in the following table.

The table is organised by the project's conceptual areas. For each area, the list reports: (i) the skill label as extracted from job advertisements in non-standard wording (Non-ESCO) and (ii) the corresponding ESCO-aligned label (ESCO). For each skill, n_job_ads indicates the number of job advertisements in which the skill was detected, and Job Ad ID(s) provide traceability to the Appendix where job-level texts and profiles are reported.

3D Printing and Additive Manufacturing

TYPE	SKILL LABEL	N_JOB_ADS	JOB AD ID(S)
Non-ESCO	3D Modeling	2	158, 194
Non-ESCO	3D Printing	0	---
ESCO	3D modelling	5	158, 162, 194, 206, 207
ESCO	additive manufacturing	0	---

Artificial Intelligence (AI) Applications

TYPE	SKILL LABEL	N_JOB_ADS	JOB AD ID(S)
Non-ESCO	Deep Learning	2	85, 94
Non-ESCO	Machine Learning	2	85, 94
Non-ESCO	AI Tool Integration	1	94
Non-ESCO	Artificial Intelligence	1	94
Non-ESCO	Computer Vision	1	85
ESCO	deep learning	2	85, 94
ESCO	machine learning	2	85, 94
ESCO	principles of artificial intelligence	2	94, 223
ESCO	computer vision	1	85

Automation and Robotics in Manufacturing

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TYPE	SKILL LABEL	N_JOB_ADS	JOB AD ID(S)
Non-ESCO	Production Monitoring	8	59, 83, 86, 92, 95, 119, 247, 258
Non-ESCO	Automation	2	253, 260
Non-ESCO	Automatic Machinery Operation	1	80
Non-ESCO	Industrial Automation	1	76
Non-ESCO	Production Line Setup	1	4
Non-ESCO	Production line operation	1	12
Non-ESCO	Robotic Manipulation	1	85
ESCO	monitor the production line	8	12, 83, 86, 95, 119, 231, 247, 257
ESCO	develop production line	3	4, 231, 295
ESCO	automation technology	2	253, 260
ESCO	monitor automated machines	1	80
ESCO	operate automated process control	1	142
ESCO	set up machine controls	1	117

Deep Digitalization Across the Value Chain

TYPE	SKILL LABEL	N_JOB_ADS	JOB AD ID(S)
Non-ESCO	Adobe Illustrator	12	1, 10, 22, 42, 98, 163, 165, 196, 206, 207, 255, 288
Non-ESCO	Data Analysis	9	46, 48, 108, 167, 219, 222, 235, 304, 311
Non-ESCO	ERP Systems	7	16, 44, 71, 84, 107, 231, 279
Non-ESCO	Documentation	5	87, 212, 227, 292, 309
Non-ESCO	Data Collection	4	47, 48, 78, 269
Non-ESCO	Database Management	4	60, 95, 176, 304
ESCO	manage standard enterprise resource planning system	14	3, 16, 44, 71, 84, 86, 99, 107, 108, 130, 198, 231, 279, 308
ESCO	perform data analysis	12	

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TYPE	SKILL LABEL	N_JOB_ADS	JOB AD ID(S)
			46, 48, 108, 125, 163, 167, 208, 219, 222, 235, 304, 311
ESCO	use CAD software	7	36, 40, 163, 171, 193, 258, 271
ESCO	product data management	6	74, 84, 88, 124, 251, 264
ESCO	provide technical documentation	6	1, 6, 32, 157, 162, 294
ESCO	manage database	5	60, 95, 176, 293, 304

Eco-Design Principles for Circularity

TYPE	SKILL LABEL	N_JOB_ADS	JOB AD ID(S)
Non-ESCO	Pattern Making	13	1, 10, 22, 34, 75, 89, 165, 167, 171, 206, 207, 287, 288
Non-ESCO	Technical Documentation	11	1, 6, 19, 32, 155, 267, 287, 288, 294, 297, 312
Non-ESCO	Circular Economy	8	32, 56, 110, 222, 223, 266, 269, 311
Non-ESCO	Fashion Design	5	1, 10, 37, 45, 207
Non-ESCO	Textile Design	5	9, 40, 45, 46, 143
Non-ESCO	Grading	4	163, 170, 228, 268
Non-ESCO	Textile Product Design	3	10, 151, 287
Non-ESCO	Eco-design	2	6, 251
Non-ESCO	Product Design	2	22, 206
Non-ESCO	Technical Documentation Management	2	34, 84
Non-ESCO	Pattern grading	1	155
ESCO	create patterns for garments	20	9, 22, 34, 42, 75, 89, 104, 145, 152, 155, 158, 163, 165, 167, 171, 196, 206, 207, 228, 288
ESCO	develop product design	10	6, 7, 22, 43, 156, 167, 206, 251, 287, 288
ESCO	produce textile designs	10	

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TYPE	SKILL LABEL	N_JOB_ADS	JOB AD ID(S)
			6, 9, 10, 40, 45, 46, 71, 95, 143, 151
ESCO	circular economy	8	32, 56, 110, 222, 223, 266, 269, 311
ESCO	design wearing apparel	8	1, 10, 37, 45, 91, 104, 207, 297
ESCO	grade patterns for wearing apparel	8	145, 155, 165, 171, 239, 249, 261, 296
ESCO	provide technical documentation	6	1, 6, 32, 157, 162, 294
ESCO	read technical datasheet	5	10, 15, 103, 248, 270
ESCO	verify product specifications	5	5, 18, 65, 228, 236
ESCO	create patterns for textile products	4	1, 7, 10, 307

Life Cycle Assessment (LCA) Expertise

TYPE	SKILL LABEL	N_JOB_ADS	JOB AD ID(S)
Non-ESCO	Data Analysis	9	46, 48, 108, 167, 219, 222, 235, 304, 311
Non-ESCO	Life Cycle Assessment (LCA)	3	32, 266, 269
Non-ESCO	Carbon Footprint Calculation	1	223
Non-ESCO	Greenhouse Gas (GHG) Accounting	1	266
Non-ESCO	LCA Modeling	1	269
ESCO	perform data analysis	12	46, 48, 108, 125, 163, 167, 208, 219, 222, 235, 304, 311
ESCO	assess environmental impact	3	32, 47, 88
ESCO	assess the life cycle of resources	3	32, 266, 269
ESCO	scientific modelling	1	269

Sustainable Materials Sourcing and Traceability

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PROJECT-RELEVANT SKILLS BY CONCEPTUAL AREA (NON-ESCO EXTRACTION AN ALIGNMENT)

TYPE	SKILL LABEL	N_JOB_ADS	JOB AD ID(S)
Non-ESCO	Supplier Management	10	37, 45, 74, 108, 124, 195, 251, 253, 304, 306
Non-ESCO	Compliance Management	6	59, 70, 88, 107, 109, 173
Non-ESCO	Material Selection	6	10, 49, 69, 70, 162, 279
Non-ESCO	Regulatory Compliance	6	8, 17, 19, 47, 168, 267
Non-ESCO	Supplier Communication	6	6, 86, 99, 163, 165, 168
Non-ESCO	Chemical Engineering	5	19, 200, 213, 216, 221
Non-ESCO	Documentation	5	87, 212, 227, 292, 309
Non-ESCO	Material Knowledge	5	22, 143, 165, 167, 290
Non-ESCO	Data Collection	4	47, 48, 78, 269
Non-ESCO	Inventory Management	4	59, 182, 183, 271
Non-ESCO	Supplier Coordination	4	38, 43, 57, 76
Non-ESCO	Textile Materials Knowledge	4	71, 168, 178, 288
Non-ESCO	Supplier Relationship Management	3	33, 229, 230
Non-ESCO	Environmental Databases	2	266, 269
ESCO	textile materials	16	9, 10, 33, 104, 128, 158, 162, 166, 178, 249, 252, 258, 259, 265, 287, 288
ESCO	supplier management	13	37, 45, 74, 108, 124, 195, 230, 251, 253, 264, 293, 304, 306
ESCO	maintain relationship with suppliers	7	33, 41, 43, 48, 84, 218, 229
ESCO	ensure compliance with safety legislation	6	51, 58, 125, 134, 146, 257
ESCO	manage inventory	6	59, 60, 182, 183, 200, 271
ESCO	product data management	6	74, 84, 88, 124, 251, 264
ESCO	supply chain management	6	44, 70, 74, 84, 166, 173
ESCO	analyse chemical substances	5	109, 200, 213, 216, 221
ESCO	manage data collection systems	5	47, 48, 78, 269, 301

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TYPE	SKILL LABEL	N_JOB_ADS	JOB AD ID(S)
ESCO	manage database	5	60, 95, 176, 293, 304
ESCO	select material to process	5	10, 49, 69, 162, 279

Textile Recycling and Upcycling Technologies

TYPE	SKILL LABEL	N_JOB_ADS	JOB AD ID(S)
Non-ESCO	Recycling	3	56, 252, 263
Non-ESCO	Textile Recycling	3	262, 291, 311
Non-ESCO	Textile Sorting	2	263, 310
Non-ESCO	Defect Repair	1	116
Non-ESCO	Industrial sewing machine repair	1	2
Non-ESCO	Recycling Process Management	1	32
ESCO	develop recycling programs	5	32, 56, 223, 252, 263
ESCO	alter wearing apparel	3	154, 180, 250
ESCO	operate recycling processing equipment	3	262, 291, 311
ESCO	sort textile items	2	263, 310

Virtual and Augmented Reality (VR/AR)

TYPE	SKILL LABEL	N_JOB_ADS	JOB AD ID(S)
Non-ESCO	Garment Simulation	1	158
Non-ESCO	Virtual Try-On	1	158
ESCO	run simulations	2	158, 258
ESCO	perform virtual simulation	1	158

Waste Management and Resource Minimization Strategies

TYPE	SKILL LABEL	N_JOB_ADS	JOB AD ID(S)
Non-ESCO	Reporting	34	38, 47, 57, 70, 125, 127, 131, 132, 140, 142, 198, 199, 209, 212, 213,

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TYPE	SKILL LABEL	N_JOB_ADS	JOB AD ID(S)
			214, 217, 219, 220, 221, 223, 227, 229, 230, 231, 232, 233, 235, 236, 237, 262, 263, 265, 268
Non-ESCO	Waste Management	4	76, 146, 222, 223
Non-ESCO	Efficiency Management	2	107, 144
Non-ESCO	Environmental Legislation	2	127, 215
ESCO	waste management	5	32, 76, 146, 222, 223
ESCO	environmental legislation	4	32, 127, 215, 246
ESCO	assess environmental impact	3	32, 47, 88
ESCO	lean manufacturing	3	3, 174, 309
ESCO	manage resources	3	92, 101, 144
ESCO	manage environmental management system	2	88, 215

How to read the summary table and why Non-ESCO and ESCO counts may differ

The summary table is organised by *conceptual area* and reports two complementary views of the same evidence:

- Non-ESCO (extracted skills)**:** these are the skill expressions as they are recognised in the job-ad text after ontology-guided extraction. They are close to the wording used by employers, and they capture how skills appear "in the wild".
- ESCO (standardised skills): these are the *mapped equivalents* of the extracted skills, translated into a common European vocabulary (ESCO) to enable comparison and aggregation across partners and countries.

For each skill label, the table reports:

- n_job_ads: the number of distinct job advertisements in which that skill was detected (after grouping); and
- Job Ad ID(s): the list of job advertisements that triggered the skill.

WHY JOB-AD REFERENCES CAN CHANGE WHEN MOVING FROM NON-ESCO TO ESCO

A key point for interpretation is that the Non-ESCO and ESCO sections are not two different datasets, but two different representations of the same underlying evidence. However, they are not expected to match perfectly one-to-one**,** because the ESCO step is a *standardisation (mapping) process*, and standardisation can change how evidence is grouped.

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There are three main reasons why the Job Ad IDs and counts can differ between Non-ESCO and ESCO:

1. *Many-to-one mapping (consolidation of synonyms or close variants)*
   Several Non-ESCO labels can map to a single ESCO concept if ESCO represents them as one broader skill. In this case, ESCO tends to merge evidence from multiple Non-ESCO labels, and the ESCO row may show:
   - *more Job Ad IDs*, because it aggregates occurrences that were previously split across different Non-ESCO labels; and/or
   - a *higher n_job_ads*, because it becomes a single "bucket" collecting more postings.
2. *One-to-many mapping (a Non-ESCO skill can be interpreted under different ESCO concepts depending on context)*
   A label like "Artificial Intelligence" is broad. Depending on what the job ad actually describes, the closest ESCO concept might be:
   - a general principle-level concept,
   - a more technical concept (e.g., machine learning, deep learning),
   - or a competence that ESCO defines differently.
     In this case, the mapping may **redistribute** job ads across ESCO categories, changing which IDs appear under each ESCO label.
3. *Best-fit standardisation (ESCO sometimes uses a concept that is* **not identical** *to the original wording)*
   ESCO is a controlled vocabulary: it does not contain an entry for every possible employer phrasing. When a perfect match does not exist, the mapping process selects the closest available ESCO concept.
   This may cause an ESCO label to include job ads where the employer used slightly different wording, if those are judged to refer to the same underlying competence once standardised.

WORKED EXAMPLE: WHY "PRINCIPLES OF ARTIFICIAL INTELLIGENCE" INCLUDES JOB AD 223 IN ESCO

In your example:

Non-ESCO extracted skills are:

- Deep Learning → Job Ads 85, 94
- Machine Learning → Job Ads 85, 94
- AI Tool Integration → Job Ad 94
- Artificial Intelligence → Job Ad 94
- Computer Vision → Job Ad 85

ESCO-aligned skills are:

- deep learning → Job Ads 85, 94
- machine learning → Job Ads 85, 94
- principles of artificial intelligence → Job Ads 94, 223
- computer vision → Job Ad 85

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The crucial difference is this line:

- Non-ESCO: **Artificial Intelligence** appears only in **Job Ad 94**
- ESCO: **principles of artificial intelligence** appears in **Job Ads 94 and 223**

This happens because *the ESCO layer is not simply repeating the original extracted label*. Instead, it is answering a different question:

“Which ESCO concept best represents the competence expressed in this job ad?”

In Job Ad **94**, the text evidently contained an AI-related requirement that was extracted as “Artificial Intelligence” (Non-ESCO) and then mapped to the closest ESCO concept “principles of artificial intelligence”.

But in Job Ad **223**, the job-ad text likely expressed an AI-related requirement using different wording, or embedded it in a broader requirement that was not extracted under the Non-ESCO label “Artificial Intelligence” (for example, it may have been expressed as part of a sustainability/circularity role requiring familiarity with AI-driven methods, digital transformation, or analytics). During ESCO standardisation, that requirement was nonetheless judged to be best represented by the ESCO concept **“*principles of artificial intelligence*”**.

So, the ESCO mapping can legitimately pull together evidence from job ads that did not share the same Non-ESCO label, because the standardisation step is designed to improve cross-country comparability by grouping ***meaning***, *not wording*.

HOW READERS SHOULD INTERPRET DIFFERENCES BETWEEN NON-ESCO AND ESCO

- Use **Non-ESCO rows** to understand how employers actually phrase and express skills in job ads (high fidelity to the source text).
- Use **ESCO rows** to understand which competences are emerging when all postings are normalised into a common European framework (high comparability, better for aggregation and curriculum planning).

When the ESCO section shows *more Job Ad IDs* for a given skill than the Non-ESCO section, it usually indicates that:

- multiple employer phrasings are being consolidated into one standard concept; and/or
- the ESCO mapping captures additional relevant job ads where the skill was present but expressed differently.

When the ESCO section shows *fewer IDs,* it usually indicates that:

- a Non-ESCO label was too broad and has been redistributed across more specific ESCO concepts; or
- the best-fit ESCO concept is narrower than the original extracted wording.

In short: *Non-ESCO counts reflect the surface language of job ads; ESCO counts reflect the standardised meaning after harmonisation***.** Both are valuable, but they serve different purposes—particularly when using the evidence to design coherent, modular training pathways aligned with project objectives

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Summary and implications for training design

Task 1.1 produced a structured, evidence-based picture of urgent and emerging skills needs linked to circularity and sustainability in the textile sector, grounded in real labour market demand. Partners carried out a coordinated manual collection of job advertisements using shared templates and keywords, ensuring relevance at national level and reducing legal/technical risks associated with automated scraping. Job-ad texts were then processed centrally: each ad was analysed through an ontology-guided extraction approach to identify non-ESCO skills, and subsequently mapped to ESCO skills to enable cross-country aggregation and consistent reporting. This workflow ensured (i) *traceability* from skills back to specific job ads, (ii) *comparability* across partner countries, and (iii) a *robust evidence base* to inform the next project phases (stakeholder validation and curriculum development).

The final table ("Project-relevant skills by conceptual area") provides a concise synthesis of the project's skill priorities and offers direct guidance for structuring training pathways. Reading the table by area highlights several key evidence points:

- **Deep Digitalization Across the Value Chain** shows high frequency and broad distribution across job ads (e.g., ERP-related competences, data analysis, database management, technical documentation, CAD-related tools). This indicates that digitalisation is not an "add-on" but a **cross-cutting baseline** for multiple roles, suggesting the need for training modules that combine textile-specific processes with data handling, documentation, and digital workflow management.
- **Eco-Design Principles for Circularity** emerges as another strong cluster (e.g., pattern making, product design, textile design, circular economy concepts, technical documentation). The evidence suggests that training should focus on **design-for-circularity competences** that connect creative and technical development tasks with documentation, specification checking, and circular product requirements. This area is particularly relevant for developing profiles able to translate circularity principles into tangible product and process decisions.
- **Sustainable Materials Sourcing and Traceability** is consistently represented (supplier management/ relationships, material selection, compliance, textile materials knowledge, data collection systems, product data management). This points to a need for training that bridges **procurement and sustainability**: not only "choosing materials", but ensuring traceability, supplier coordination, regulatory compliance, and data-driven product information management.
- **Waste Management and Resource Minimization Strategies** contains both specific competences (waste management, environmental legislation, lean manufacturing, resource management) and a very high-frequency "Reporting" signal. This suggests that sustainability work in companies is strongly linked to **monitoring, documentation, and reporting practices**. Training should therefore include practical elements on sustainability documentation/reporting routines, KPI logic, and operational resource efficiency—anchored in the language and constraints of manufacturing environments.
- **Textile Recycling and Upcycling Technologies** appears with a smaller but meaningful set of skills (recycling programs, recycling processing equipment, sorting textile items, repair/alteration-related competences). This indicates that recycling-related roles may be **more specialised and less frequently advertised**, but strategically central to the project. Training here should be modular and practice-oriented, targeting operational know-how (sorting, processing, quality sorting criteria) while connecting to traceability and circular economy requirements.

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SUMMARY AND IMPLICATIONS FOR TRAINING DESIGN

- **Automation and Robotics in Manufacturing**, and **Artificial Intelligence (AI) Applications**, are present as emerging clusters (production monitoring, automation technology, monitoring automated machines; plus AI/ML/deep learning and computer vision). Their frequency suggests these competences are currently more concentrated in specific roles, but they represent clear signals of the **twin transition** in the sector. Training implications include advanced/specialisation tracks (rather than baseline training) focusing on how automation/AI supports process monitoring, defect detection, predictive maintenance, and production optimisation.
- **Virtual and Augmented Reality (VR/AR)** and **3D Printing / Additive Manufacturing** show limited occurrences, but they are strategically relevant as innovation enablers (e.g., garment simulation and virtual try-on; 3D modelling). These signals suggest that training in these areas may be best framed as **pilots or optional advanced units**, integrated into design/development pathways rather than treated as stand-alone core modules.

Overall, the table supports a training architecture built on **three layers**: (1) cross-cutting foundations (digital workflow + documentation + data literacy; compliance and traceability principles), (2) core circularity competences (eco-design for circularity; sustainable materials sourcing; resource minimisation), and (3) specialised innovation modules (recycling technologies; automation/robotics; AI; VR/AR and 3D where relevant). This structure is coherent with the project's objectives because it reflects both the **frequency of market demand** (what is already widely required) and the **strategic direction of transformation** (what is emerging and critical for the transition), providing a concrete, evidence-driven basis to design learning pathways and modular training content aligned with Skills4Circularity priorities.

Annexes

This report is accompanied by two annexes containing the full underlying job-advertisement data referenced in the analysis. Given the volume of this material, it is not reproduced in this document and is available from the project team upon request.

Annex I – Job Advertisement Scraping Results, by Country

Annex II – Register of Job Advertisements by Identifier

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Upskilling and reskilling the textile industry sector to face the challenges in recycling, traceability and certification of recycled products