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Sustainability-Related Skills for the Green Transition: AI-Enabled Assessment, Curricula Revision Across All Educational Levels, and Upskilling/Reskilling Pathways for Labour Market Participation

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Abstract

The transition to a sustainable economy depends on transforming the workforce at least as quickly as the labour market is being reshaped by automation. This chapter examines how artificial intelligence (AI) can identify the competencies required to deliver the United Nations Sustainable Development Goals (SDGs) and can guide the revision of curricula across all levels of education, while critically assessing the risks that accompany technology-driven workforce planning. Drawing on an operational natural-language-processing framework that extracts skills from policy documents and curricula, maps them to the European ESCO taxonomy and to SDG targets—achieving an overall F1 score of 0.963 for skills extraction and 0.809 for environmental-SDG alignment in an authors' evaluation—we show how AI can accelerate the skills intelligence needed for evidence-based upskilling and reskilling. We weigh these promises against the perils of algorithmic bias, linguistic and regional exclusion, worker displacement, surveillance and rebound effects, and we propose governance and educational pathways for an inclusive transition that genuinely empowers labour-market participation.

Keywords: *sustainability skills; green transition; artificial intelligence; upskilling and reskilling; curricula reform; Sustainable Development Goals; ESCO; just transition.*

1. Introduction

The twin green and digital transitions have moved from political aspiration to operational necessity. Meeting the United Nations 2030 Agenda requires not only new technologies and capital, but a workforce able to design, deploy, operate and govern them. Human-capital capacity is increasingly recognised as one of the principal constraints on the pace of sustainable transformation, alongside technology and finance. The International Labour Organization estimates that the shift to a greener economy could create twenty-four million new jobs worldwide by 2030, yet these opportunities depend entirely on whether workers possess the relevant competencies, and whether education and training systems can supply them in time (International Labour Organization 2018).

The difficulty is one of both scale and speed. Sustainability-related competencies are dispersed across occupations and sectors, evolve rapidly, and are frequently implicit in policy and regulation rather than codified in curricula. Traditional methods of skills assessment—manual analysis anchored in static taxonomies—often struggle to keep pace with the rate at which green and digital roles are emerging and being redefined. This is precisely the terrain on which a disruptive technology such as artificial intelligence presents a paradox that sits at the heart of this volume. The same natural-language-processing systems that can read thousands of policy documents in hours, and translate abstract sustainability goals into concrete competency requirements, also threaten to displace workers faster than reskilling systems can respond, to encode historical inequalities in ostensibly neutral assessments, and to concentrate the benefits of the transition among those already advantaged.

This chapter argues that AI should be treated as an amplifier of policy choices rather than an autopilot for them. Deployed with appropriate governance, AI-assisted skills intelligence can make the transition faster and fairer; deployed uncritically, it can entrench exclusion. We develop this argument in three movements. First, we characterise the sustainability skills gap and why conventional approaches struggle. Second, drawing on an operational framework developed and deployed by the authors within the UN SDSN Global Climate Hub, we set out the concrete promises of AI-enabled skills assessment, together with an empirical evaluation and an illustrative policy case study. Third, we subject the same technology to critical scrutiny—examining bias, exclusion, displacement, surveillance and rebound effects—before proposing curricula reforms across all levels of education and governance pathways for an inclusive transition.

2. Sustainability-Related Skills and the Scale of the Gap

Sustainability-related skills—often termed "green skills"—comprise the knowledge, abilities and values that enable individuals to work and live in ways that reduce environmental harm and support sustainable development. They range from technical competencies in renewable-energy systems, circular-economy design, sustainable agriculture and green finance, to transversal capacities such as systems thinking, futures literacy and the ability to act on complexity and uncertainty. The European Commission's GreenComp framework codifies the latter into four competency areas, underlining that sustainability is not a narrow technical specialism but a cross-cutting capability required throughout the labour market (Bianchi, Pisiotis, and Cabrera Giráldez 2022).

The scale of the required transformation is considerable. The European Skills Agenda envisages large-scale upskilling and reskilling to meet green and digital demands over the present decade (European Commission 2020). Yet supply is misaligned with demand at every level.

Curricula—from primary schooling through vocational training to university degrees—typically lag labour-market needs by years, and rarely integrate sustainability competencies in a systematic way. Policy documents articulate ambitious goals without operationalising the specific skills that their implementation demands, producing a persistent gap between aspiration and delivery.

Compounding this is a time-criticality problem: the cadence of traditional curriculum reform is measured in years, whereas the 2030 horizon and the pace of technological change demand responsiveness measured in months. There is also a measurement problem that precedes it. Because sustainability requirements are frequently embedded in regulation, procurement rules and technical standards rather than in job descriptions, the competencies they imply are often invisible to the instruments—occupational surveys, employer panels, periodic curriculum review—that education systems conventionally use to detect demand. It is this combination—a large, dispersed, fast-moving and largely implicit set of requirements—that makes purely manual approaches to skills intelligence difficult to sustain, and that motivates the AI-assisted methods examined next.

3. AI-Enabled Assessment of Sustainability Skills: Promises and Capabilities

Recent advances in natural language processing, and in particular transformer-based language models (Vaswani et al. 2017), make it possible to extract and analyse competencies from unstructured text at a scale and granularity that were previously unattainable. To ground the discussion in a concrete system rather than in abstract potential, we draw on a framework developed by the authors and colleagues and deployed operationally within the UN SDSN Global Climate Hub as the “AE4RIA AI Skills Tool”. A publicly accessible implementation and an accompanying quick-start guide are available through the AE4RIA website (AE4RIA 2026), and the architecture of the underlying system is documented in a publicly available preprint (Koundouri, Landis, and Feretzakis 2025). The current public version accepts English-language

HTML documents and presents the extracted skills, the associated ESCO occupations, recommended learning resources and alignment with the seventeen SDGs; uploaded files are processed in memory and are not stored.

3.1 How the framework works

The underlying research pipeline processes textual document content across several formats, while the current publicly accessible web implementation accepts English-language HTML files only; the description that follows refers to the research pipeline. It reads a document, segments it into semantically coherent passages of roughly 120 words, and encodes each passage using a sentence-transformer model that produces 384-dimensional embeddings. These embeddings are compared, via efficient similarity search over a FAISS index (Johnson, Douze, and Jégou 2019), against the European Skills, Competences, Qualifications and Occupations (ESCO) taxonomy, comprising 13,890 skills and 3,008 occupations in the release used for this evaluation. Passages whose cosine similarity to a skill exceeds an empirically tuned threshold are retained, and syntactic analysis of verb–object patterns captures implicit competencies—phrases such as "coordinate international logistics" or "analyse environmental data"—that keyword matching would miss. Extracted skills are then aligned to occupations, matched to curated courses from the SDG Academy and the AE4RIA network to surface concrete reskilling pathways, and scored for their thematic alignment with each of the seventeen SDGs. Crucially, the system is designed as a human-in-the-loop decision-support tool: its outputs are intended to augment expert judgement, not to replace it.

3.2 Evaluation design and provenance of the reported results

The performance figures reported below derive from an evaluation conducted by the authors during development of the framework. Two sources should be distinguished. The system architecture is set out in a publicly available preprint (Koundouri, Landis, and Feretzakis 2025), which reports an earlier evaluation of the skills-extraction component alone; the figures given below, including all SDG-alignment results, come from a subsequent and more extensive evaluation described in a companion manuscript currently under review (Koundouri et al., under review). Readers wishing to examine the method independently should consult the former, while the specific values in Tables 1 and 2 are drawn from the latter. Because these results underpin much of the argument that follows, the evaluation design warrants brief description here rather than being taken on trust.

The evaluation corpus comprised two components. The first was a set of eighty purpose-built synthetic documents, divided equally between texts containing explicit skill statements and texts in which skills were referenced only implicitly, incorporating two hundred curated ESCO skills spanning technical, managerial and cross-cutting categories. The second was a set of one hundred and twenty real-world policy documents drawn from the European Commission, the European Parliament and other regulatory bodies, covering environmental regulation, digital-transformation initiatives and workforce-development strategies. Ground-truth annotations for both skill identification and SDG alignment were produced by annotators with professional backgrounds in human resources, sustainability and policy analysis. Precision, recall and F1 were computed against these annotations, with a skill recorded where cosine similarity to an ESCO skill embedding exceeded a threshold of 0.35, tuned empirically to balance precision against recall.

Three limitations of this design should be stated at the outset, since they bear directly on the critical discussion in Section 6. The corpus is European and English-language throughout, so the reported figures do not evidence performance in other linguistic or institutional settings. While the annotation was performed by domain experts, it was not independently replicated, so interannotator agreement is not reported. And the figures below are aggregated across the synthetic and real-world subsets rather than disaggregated between them, so the contribution of each to overall performance cannot be separated here. The results should therefore be read as a credible indication of feasibility within a specific context, not as a general performance guarantee.

3.3 Empirical performance

On this corpus the framework achieved strong performance against the expert-annotated reference set for both explicit and implicit skills, with an overall F1 score of 0.963 and consistently strong results for the green and digital competencies most relevant to the transition (Table 1). It should be emphasised that these figures express agreement with expert-produced annotations rather than equivalence to expert performance, which was not tested. The margin between explicit and implicit detection is nonetheless instructive: implicit skills are recovered at F1 = 0.947, which is precisely the capability that conventional keyword-based methods often handle poorly and that matters most when competencies are buried in regulatory language.

Table 1. Skills-extraction performance by category (authors' evaluation; 80 synthetic and 120 real-world policy documents).

Skill category	Precision	Recall	F1
Explicit skills	0.992	0.963	0.976
Implicit skills	0.921	0.975	0.947
Green skills	0.938	0.952	0.945
Digital skills	0.954	0.967	0.960
Overall	0.956	0.969	0.963

The dedicated SDG-alignment module performs best precisely where the green transition is most demanding. Environmental goals are detected most reliably (F1 = 0.809), while performance on social goals is lower—an informative asymmetry that reflects the current predominance of environmental language in policy corpora and training data, and that signals where datasets must be expanded (Table 2). Recall is high across all categories while precision is more modest, a profile appropriate to a screening instrument that surfaces candidates for expert review rather than one that issues final determinations.

Table 2. SDG-alignment detection performance by category (authors' evaluation).

SDG category	Precision	Recall	F1
Environmental (SDGs 6, 7, 13, 14, 15)	0.724	0.916	0.809
Economic (SDGs 8, 9, 11, 12)	0.703	0.921	0.797
Social (SDGs 1–5, 10, 16)	0.682	0.887	0.771
Partnership (SDG 17)	0.651	0.843	0.735
Overall	0.690	0.892	0.778

3.4 What this enables

Three capabilities follow directly, and each maps onto a lever for the transition. First, near-real-time policy-to-skills translation: a lengthy regulation can be converted into an explicit competency profile in a fraction of the time manual analysis would require, allowing training provision to be aligned with new obligations as they are enacted. Second, systematic curriculum-gap analysis: the same machinery can read a curriculum or a national qualification standard and reveal, in a structured way, which sustainability competencies it omits relative to labour-market demand. Third, personalised reskilling pathways: by matching an individual's or a region's competency profile against SDG-aligned courses, the system can recommend the specific learning needed to close observed gaps. The promise, in short, is scale, speed and granularity—turning skills intelligence from a periodic, manual exercise into a continuous, evidence-based input to workforce and education policy.

4. Illustrative Case Study: Sustainability Competencies in the EU Deforestation Regulation

The value of policy-to-skills translation is best illustrated concretely. The EU Deforestation Regulation (Regulation (EU) 2023/1115) requires that a range of commodities placed on the Union market be deforestation-free, and imposes due-diligence, traceability and geolocation obligations across complex global supply chains. Its successful implementation depends on competencies that the regulation itself never enumerates. Applying the framework to the European Commission's policy text on minimising deforestation associated with products placed on the EU market, the system processed the long-form document in under thirty seconds in the authors' implementation test, and produced an actionable competency profile (Table 3). This timing is reported as an indication of practical feasibility rather than as a benchmark, since it depends on hardware, document length and whether models and indexes are preloaded.

Table 3. Outputs of the framework applied to the EU deforestation policy text (authors' analysis).

Output dimension	Result
Distinct skills identified	31, including carbon-footprint assessment, intermodal logistics coordination and environmental-compliance management
Strongest SDG alignment	SDG 13 Climate Action (0.92); SDG 9 Industry, Innovation and Infrastructure (0.89); SDG 11 Sustainable Cities and Communities (0.85)
Closest ESCO occupations	Environmental logistics coordinator; sustainable transport planner (8 occupation matches in total)
Recommended learning	12 SDG Academy courses focused on sustainable logistics
Processing time	Under 30 seconds for the full document

The significance of this output lies less in any single figure than in the translation it performs. An instrument written in the language of trade and environmental law was rendered, automatically, into the language of skills, occupations and courses—the form in which ministries of education, training providers and employers can act. A single regulation thus becomes a concrete input to curriculum design and reskilling provision, achieved in seconds rather than the weeks of expert effort the equivalent manual analysis would require. Readers may explore the workflow directly: the public implementation supplies sample European policy documents, including an anti-deforestation proposal, that can be run through the tool (AE4RIA 2026). It is worth noting what the system did not do: it did not determine which of the thirty-one competencies are scarce in a given labour market, nor which regions lack provision, nor whether the recommended courses are of adequate quality. Those judgements remain human, and the tool's value depends on their being exercised.

A second domain points in the same direction from the opposite end of the policy chain. Renewable-energy deployment across Europe depends on occupations—wind-turbine technicians, grid-integration engineers, heat-pump installers, energy auditors—for which training capacity has consistently lagged installation targets (International Renewable Energy Agency and International Labour Organization 2024). Here the constraint is not that the required competencies are unknown, but that they are defined inconsistently between national qualification systems and revised more slowly than technology and regulation change. Automated mapping of national training standards against a common taxonomy such as ESCO offers a tractable route to identifying precisely where provision falls short and in which regions: the same operation performed above on legislation, applied instead to curricula and qualification frameworks. We present this as an indicative application rather than a completed empirical study; the deforestation analysis above is the single case for which evaluated results are reported here.

5. Curricula Revision Across All Educational Levels

Skills intelligence is only useful if education systems can act on it. Empowering labour-market participation in the transition therefore requires curricula reform that is coordinated across the whole educational pathway, not confined to a single stage. AI-derived demand signals of the kind described above can inform each level, but the pedagogical work of embedding sustainability competencies remains distinct at each.

At the **primary** level, the priority is foundational: cultivating environmental literacy, curiosity and early systems thinking, so that children come to see the natural, social and economic worlds as interconnected. **Secondary** education can build on this by integrating climate science, circular-economy principles and sustainable development into core subjects rather than treating them as optional add-ons, and by developing the numeracy and data literacy that green and digital roles increasingly require. **Vocational education and training** is arguably the most time-critical: programmes must be modernised rapidly to cover renewable-energy systems, energy efficiency, sustainable construction and green digital tools, since much of the near-term transition workforce will come through this route rather than through universities.

Higher education has a dual task—embedding sustainability across every discipline, from engineering and economics to law and medicine, while also offering specialised programmes at the frontier of the field. Beyond initial education, **lifelong learning** becomes the principal mechanism for a workforce that must reskill repeatedly over a career: modular micro-credentials, stackable certificates and portable skills passports allow workers to acquire and evidence specific competencies without withdrawing from the labour market for extended periods. Underpinning all of this is **teacher training**: educators cannot teach systems thinking, sustainability and the responsible use of digital tools unless they are themselves equipped to do so, which makes continuing professional development for teachers a precondition for reform rather than an afterthought.

Across every level, the pedagogical centre of gravity must shift from the transmission of static knowledge towards competency-based, problem-oriented and interdisciplinary learning—precisely the capacities that a fast-moving, uncertain transition demands. Here AI can help operationally, by keeping the demand-side picture current so that curricula are revised against real labour-market signals rather than against assumptions that are already out of date. The mechanism is worth stating plainly, because it is where the technical apparatus of Section 3 meets institutional practice: a curriculum or qualification standard is processed exactly as a policy document is, its competency profile is compared against the profile derived from current regulation and labour demand, and the difference between the two constitutes a structured, auditable statement of what the curriculum omits. This converts curriculum review from an episodic exercise dependent on committee judgement into a continuous one supported by evidence—provided, as Section 7 argues, that the evidence is treated as an input to deliberation rather than as its conclusion.

6. Perils and Critical Analysis

The capabilities set out above are genuine, but so are their attendant risks, and a critical account must give the perils equal weight. Several are structural rather than incidental.

Algorithmic bias and inequality. Language models learn from historical data, and historical labour markets are unequal. Left unaudited, skills-assessment systems can reproduce and even amplify existing patterns of disadvantage—by gender, class, disability or region—under a veneer of technical objectivity (Bolukbasi et al. 2016; Bender et al. 2021). A tool that allocates opportunity must therefore be treated as a site of distributive justice, not merely of engineering.

Linguistic and regional exclusion. The framework examined here, like most such systems, was optimised for European contexts and English-language documents, a limitation stated explicitly in Section 3.2. This is not a minor caveat. If skills intelligence performs well in dominant languages and poorly in others, it risks channelling investment and opportunity towards already-advantaged regions and workers, deepening rather than narrowing divides—an acute concern for smaller linguistic communities, including Greek and other less-resourced languages, and more acute still for the low- and middle-income countries where the SDG agenda is most demanding.

Displacement faster than reskilling. The economic literature is clear that automation both displaces and reinstates labour, and that the net and distributional effects depend on the balance between the two and on the speed of adjustment (Frey and Osborne 2017; Acemoglu and Restrepo 2019). The central danger is temporal: even where new green and digital roles are created, there is no guarantee that displaced workers will have the skills, resources or geographic proximity to move into them before hardship sets in. Skills intelligence that identifies gaps is of little help to a worker who lacks the means or the time to close them.

Validity, surveillance and environmental cost. Three further risks deserve mention. First, algorithmic confidence is not competence: a high similarity score indicates textual alignment, not verified capability, and treating the former as the latter would be a category error with real consequences for individuals—an error the modest precision figures in Table 2 make concrete rather than hypothetical. Second, continuous skills monitoring shades easily into workforce surveillance, raising acute questions of privacy, consent and power that data-protection law only partly answers. Third, the transition's own tools have an environmental footprint: training and running large models consumes significant energy and water (Strubell, Ganesh, and McCallum 2019; Luccioni, Viguier, and Ligozat 2023; Li et al. 2023), so that AI deployed for sustainability can, through rebound effects and unchecked compute growth, work against the very goals it serves. Each of these is a reason not to abandon the technology, but to govern it.

7. Governance and Policy Pathways for an Inclusive Transition

Whether AI-assisted skills intelligence narrows or widens inequality is not a property of the technology but of the choices that surround it. Five governance commitments would tilt the balance towards inclusion.

First, a **just-transition** frame should be explicit, ensuring that displaced workers and vulnerable communities are supported—through income security during reskilling, active labour-market policy and regional investment—so that no group bears the cost of a transition undertaken for the common good. Second, **human-in-the-loop** design should be the norm rather than the exception, with automated outputs treated as decision support subject to expert and, where appropriate, worker review. The distinction matters institutionally as well as ethically: a system that recommends is answerable to those who act on its recommendations, whereas a system that decides displaces accountability into the model itself.

Third, systems should be built for **inclusion by design**: multilingual and regionally adapted taxonomies, routine bias audits disaggregated by the characteristics along which exclusion is likely, transparency about limitations of the kind set out in Section 3.2, and privacy-preserving techniques such as federated learning that keep sensitive data local. Fourth, delivery depends on **partnership**—between government, industry, education providers and social partners—both to ensure that training reflects genuine labour-market demand and to guarantee that access to reskilling infrastructure is equitable rather than concentrated among those already advantaged.

Fifth, all of this must sit within a coherent **regulatory** framework. The EU Artificial Intelligence Act (Regulation (EU) 2024/1689) classifies specified AI systems used in employment, worker management, recruitment and access to certain educational or vocational opportunities as high-risk, subject to the conditions and exclusions laid down in the Regulation; data-protection law governs the monitoring that continuous skills assessment involves. Whether a particular skills-intelligence deployment falls within these categories depends on its purpose and use, and deployers should assess this rather than assume it either way. Finally, success should be measured by more than employment rates—by equity of access, quality of work and well-being—so that the metric does not quietly redefine an inclusive goal as a merely quantitative one.

8. Conclusion

The sustainability transition will be delivered, or not, by people. This chapter has argued that artificial intelligence can materially accelerate the skills intelligence on which that delivery depends: an operational framework can translate policy into competencies, expose the gaps in curricula, and point workers towards the learning that closes them, at a speed and scale beyond manual methods. The empirical results reported here—an overall F1 of 0.963 for skills extraction and strong environmental-SDG alignment—show that this is demonstrable rather than speculative, within the European, English-language context in which it was evaluated.

Yet the same technology can exclude as efficiently as it can empower. Bias, linguistic and regional narrowness, displacement outpacing reskilling, spurious validity, surveillance and rebound effects are not reasons to reject AI, but they are decisive reasons to govern it—through just-transition principles, human oversight, inclusive design, genuine partnership and proportionate regulation. Treated as an amplifier of deliberate policy rather than an autopilot, and as a decision-support tool that augments rather than replaces human judgement, AI can help make the transition both faster and fairer. As the 2030 horizon approaches, the task is not to choose between technological optimism and caution, but to build the institutions that let us have the benefits of the former while taking seriously the warnings of the latter—so that sustainability-focused workforce transformation genuinely widens labour-market participation instead of narrowing it.

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