



Work Package 2

DELIVERABLE 5

REVIEW AND ASSESS REPORT

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TABLE OF CONTENTS

1. Introduction.....	3
Structure and Scope.....	3
Task-to-Deliverable Mapping	4
Leadership and Contributions.....	4
2. Methodology.....	4
2.1. Landscape Review Methodology.....	4
2.2. Classification of AI Integration.....	5
2.3. In-Depth Curriculum Analysis.....	6
2.4. Stakeholder Consultation Design	6
3. The Landscape of AI and Sustainability Education	7
3.1. Geographic Distribution	7
3.2. Programme Types and Structure.....	8
3.3. Thematic Classification of Programmes.....	8
3.4. AI Integration Across the Landscape	9
3.5. Curricular Content and Pedagogical Orientation	12
3.6. Strengths and Weaknesses of the Current Landscape	14
4. Design Conventions and Standards	15
4.1. Structural Standards and Credit Frameworks.....	15
4.2. Delivery Modes and Teaching Approaches	16
4.3. Assessment Approaches and Practices	18
4.4. Admission Standards and Entry Pathways.....	20
4.5. Summary of Common Approaches	21
5. Content Analysis, Gap Analysis, and Framework Assessment.....	22
5.1. Content Analysis of Programmes with Core AI Integration.....	22
5.2. Gap Analysis	27
5.3. Assessment of Existing Micro-Credential Frameworks.....	29
6. Design Recommendations	31
6.1. Identify Learning Outcomes Aligned with Participant Backgrounds	31
6.2. Develop an Assessment Strategy Aligned with Targeted Competences	32
6.3. Define Inclusive Course Structures.....	33
6.4. Create a Supportive Learning Environment	33
6.5. Define a Modular Credit Architecture.....	33

6.6. Build Transparency and Quality to Foster Recognition	34
6.7. Curriculum Architecture: Maturity-Based Tiers.....	34
6.8. Addressing Content Gaps	35
6.9. Competence Framework for Learning Outcome Development	35
7. Positioning Within Existing Micro-Credential Offerings	36
8. Stakeholder Consultation Results.....	38
8.1. AI and Data Science Profile	38
8.2. Engineering and Design Profile	42
8.3. Social Sciences and Management Profile.....	43
8.4. Companies and Organisations Profile	48
8.5. Cross-Profile Patterns and Implications for Design.....	52
8.6. Current Status and Next Steps	53
9. Conclusion	54
References	55
Academic Literature	55
Labour Market and Industry Reports.....	55
European Policy and Quality Assurance Frameworks.....	55
Programme Data	56
Appendix A: Programmes with Core AI	56
Appendix B: Micro-Credential and Short-Course Programmes	58
Appendix C: Stakeholder Consultation Questionnaires	60
C.1. AI and Data Science Profile	60
C.2. Engineering and Design Profile.....	63
C.3. Social Sciences and Management Profile	66
C.4. Companies and Organisations Profile	69

1. Introduction

The RADAR-aim project (**Review, Assess, Develop, Adopt, and Reflect** on AI & Sustainability Micro-credential courses) brings together five partners across four European countries to address a critical gap in sustainability education: the limited integration of artificial intelligence competencies into postgraduate programmes. Work Package 2 (Review and Assess), led by NOVA IMS, has conducted a comprehensive examination of the global sustainability education landscape, identified the design standards and practices that shape contemporary offerings, assessed the suitability of existing frameworks for micro-credential development, and gathered stakeholder feedback to inform design recommendations.

This Research Process Report consolidates the full body of work undertaken across Work Package 2, bringing together four complementary deliverables into a single, self-contained account. It is designed for external partners, policymakers, and educational institutions who require a comprehensive overview of the review, assessment, and design process without needing to consult the individual deliverables.

Structure and Scope

This report is organised as follows:

- **Section 2: Methodology** integrates the research approaches used across all four work streams: the landscape review methodology, the classification framework for AI integration, the in-depth curriculum analysis methodology, and the stakeholder consultation design.
- **Section 3: The Landscape of AI and Sustainability Education** presents the comprehensive mapping of 345 postgraduate programmes across 32 countries, their geographic distribution, programme types, thematic classification, and patterns of AI integration.
- **Section 4: Design Conventions and Standards** identifies the common structural, pedagogical, and assessment approaches used in existing programmes, with particular attention to the 31 programmes identified as having core AI integration.
- **Section 5: Content Analysis, Gap Analysis, and Framework Assessment** examines the curriculum content of the 31 core AI-integration programmes, identifies systematic gaps in teaching coverage, and evaluates the suitability of existing European micro-credential frameworks.
- **Section 6: Design Recommendations** presents nine specific, evidence-based recommendations for the design of the RADAR-aim micro-credential offering.
- **Section 7: Positioning Within Existing Micro-Credential Offerings** situates the RADAR-aim programme within the emerging landscape of formal micro-credentials.
- **Section 8: Stakeholder Consultation Results** reports findings from consultation with four stakeholder profiles: AI and Data Science specialists, Engineering and Design professionals, Social Sciences and Management experts, and Companies and Organisations.

- **Section 9: Conclusion** provides a unified conclusion summarising the achievements of Work Package 2 and its foundation for subsequent work.

Task-to-Deliverable Mapping

Work Package 2 comprised nine tasks, each corresponding to elements of this report:

Task	Title	Section
T2.1	Identify and characterise sustainability-related postgraduate programmes	Section 3
T2.2	Analyse common approaches and standards in programme design	Section 4
T2.3	Analyse the content of programmes with core AI integration	Section 5
T2.4	Identify gaps in the AI-sustainability education landscape	Section 5
T2.5	Assess existing micro-credential frameworks	Section 5
T2.6	Conduct stakeholder consultation	Section 8
T2.7	Develop design recommendations	Section 6
T2.8	Position RADAR-aim within existing offerings	Section 7
T2.9	Synthesis findings and produce research process report	Section 9

Leadership and Contributions

Work Package 2 was led by Universidade Nova de Lisboa (NOVA), with Università degli Studi di Roma Tor Vergata (Tor Vergata) providing active support throughout. NOVA prepared the majority of work package activities drawing on inputs from all consortium partners, with Tor Vergata conducting initial reviews; conversely, Tor Vergata coordinated the Gap Analysis and Stakeholder Consultation, with initial review provided by NOVA. Both partners presented findings to the full consortium for discussion. The work package culminated in a two-day co-creation workshop in Lisbon, integrating insights from tasks T2.1 through T2.6 into the Design Recommendations (T2.7). Following the workshop, all consortium partners contributed to the stakeholder consultation (T2.8), with both lead partners ensuring proper documentation and reporting (T2.9) throughout the work package.

2. Methodology

This section synthesises the research methodologies employed across all four analytical work streams of Work Package 2: the landscape review (Task T2.1), the analysis of common approaches and standards (Task T2.2), the content analysis and gap assessment (Tasks T2.3–T2.5), and the stakeholder consultation (Task T2.6).

2.1. Landscape Review Methodology

The landscape review employed a systematic search approach combining multiple data sources to ensure comprehensive coverage of the global educational landscape. Three international programme databases were used as primary sources: study.eu, mastersportal.com, and education.com. These platforms aggregate programme information from universities across

Europe and beyond, providing standardised descriptions that facilitate comparative analysis. To complement the international databases and capture programmes not listed on English-language platforms, three national databases were also consulted, covering programmes in Portugal, Spain, and Italy.

The search strategy combined primary and secondary search terms to capture both explicitly labelled programmes and those with embedded but less visible AI or sustainability components:

- **Primary search terms:** “sustainability” OR “sustainable” combined with “artificial intelligence” OR “AI” OR “machine learning”
- **Secondary search terms:** “circular economy,” “green,” “smart cities”

This dual-term approach was designed to identify programmes that may address AI-sustainability intersections without explicitly using those terms in their titles, capturing relevant offerings in fields such as urban planning, environmental engineering, and resource management.

Inclusion criteria: Programmes were included in the review if they met the following criteria: (i) postgraduate level (Master’s degree or equivalent); (ii) offered by an accredited higher education institution; (iii) containing sustainability-related content as a substantive component of the curriculum; and (iv) programme information publicly available in sufficient detail to allow classification.

Data extraction: For each identified programme, standardised data were extracted across eight fields: degree type, title, country, university, key courses, programme overview, AI integration category, and URL. This extraction framework was applied consistently across all 345 programmes.

2.2. Classification of AI Integration

Each of the 345 programmes identified in the landscape review was classified into one of three integration levels based on a structured review of published curricula and programme descriptions:

- **Core integration:** Programmes that embed AI, machine learning, or data science methods as mandatory, substantive components of the curriculum. These programmes typically feature multiple dedicated modules on computational methods and position AI techniques as central tools for addressing sustainability challenges.
- **Peripheral integration:** Programmes that include AI-related content in an optional or supplementary capacity, such as a single elective module on data analytics or a brief introduction to computational methods within a broader sustainability course.
- **No integration:** Programmes focused exclusively on sustainability domain knowledge without any AI or computational content in the published curriculum.

This classification was applied consistently across all 345 programmes based on publicly available information (syllabi, course lists, and programme descriptions). The key distinction between Core and Peripheral rests on whether AI methods are mandatory and structurally embedded (Core) or optional and supplementary (Peripheral).

The classification yielded 31 programmes with Core AI integration, 19 with Peripheral integration, and 295 with no AI content. The 31 Core programmes met two additional criteria for inclusion in

the in-depth analysis: sufficient publicly available documentation (detailed syllabi, course descriptions, learning outcomes, and assessment information) and thematic alignment (core focus at the intersection of AI/data science and sustainability). The 31 programmes span 11 countries, 27 universities, and both one-year (18 programmes) and two-year (13 programmes) structures.

2.3. In-Depth Curriculum Analysis

The 31 programmes with core AI integration were subjected to detailed individual examination. For each programme, researchers visited the institution's official website and systematically extracted all publicly available curriculum information, including programme descriptions, module-level syllabi, stated learning objectives, teaching methodologies, assessment methods, and expected outcomes. Where institutions published detailed course catalogues or study plans, these were reviewed at the individual module level to capture the specific AI techniques and sustainability topics covered.

Data extraction followed a standardised template covering eight analytical dimensions: AI techniques and methods taught, alignment with the Sustainable Development Goals, stated learning outcomes, teaching and delivery methodologies, assessment formats, admission requirements, programme duration and credit structure, and thematic category. This structured approach ensured comparability across programmes from different institutional and national contexts, while allowing the depth of extraction to vary with the level of detail available in each institution's published materials.

2.4. Stakeholder Consultation Design

The stakeholder consultation was designed to validate, refine, and extend the design recommendations derived from the landscape, standards, and content analyses. The consultation engaged four distinct stakeholder profiles:

- **AI and Data Science specialists:** Academics and practitioners with primary expertise in AI, machine learning, data science, and related computational methods
- **Engineering and Design professionals:** Engineers, architects, and design specialists working on sustainability-focused technical challenges
- **Social Sciences and Management experts:** Social scientists, policy specialists, business school academics, and governance experts
- **Companies and Organisations:** Representatives from private sector, public sector, and non-profit organisations employing sustainability professionals

For each profile, a customised questionnaire was developed, grounded in a common competence framework but adapted to the specific perspective and expertise of each group. Questionnaires covered learning outcomes and competences, curriculum structure and progression, delivery modes and support, assessment and recognition, and implementation priorities. The consultation was conducted online using standardised survey instruments, with complementary interviews conducted with selected respondents to capture nuanced feedback and contextual insights.

3. The Landscape of AI and Sustainability Education

The landscape review mapped 345 postgraduate programmes across 32 countries, identifying their geographic distribution, programme types, thematic orientation, and patterns of AI integration. This section presents the resulting landscape, providing the empirical foundation for all subsequent analysis and recommendations.

3.1. Geographic Distribution

The 345 sustainability programmes identified span 32 countries but are concentrated heavily in Western and Northern Europe. The geographic distribution reflects both the maturity of sustainability education in different regions and the linguistic reach of the databases consulted.

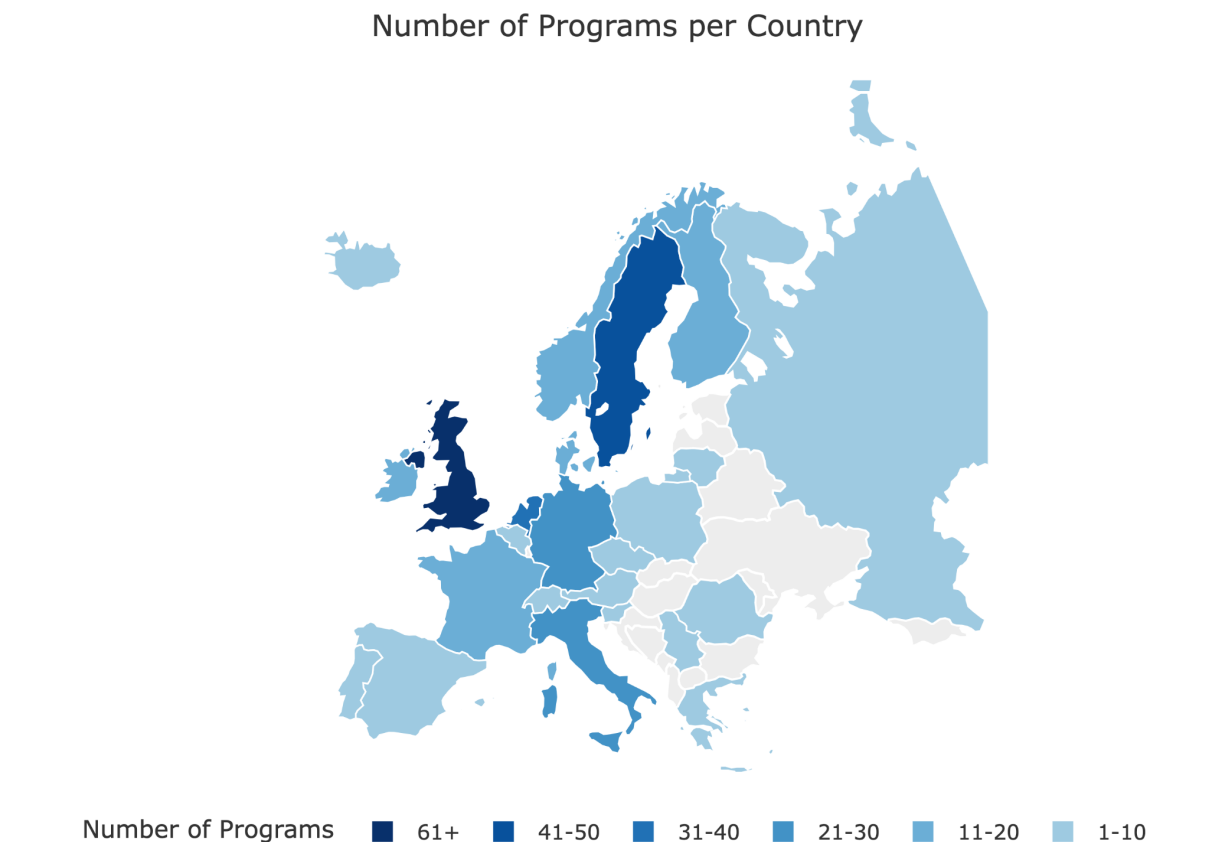


Figure 1: Geographic distribution of 345 sustainability-focused postgraduate programs across 32 countries.

The United Kingdom leads with 62 programmes (18.0% of the total), followed by Sweden with 43 (12.5%), the Netherlands with 40 (11.6%), Germany with 28 (8.1%), and Italy with 25 (7.2%). The Nordic countries are disproportionately well represented: collectively, Sweden, Finland (20), Norway (16), Denmark (12), and Iceland (2) account for 93 programmes (27% of the total), reflecting strong governmental commitment to sustainability education and digital innovation despite representing only 3% of Europe's population.

Ireland (20 programmes) and France (18) show substantial offerings, while Central and Eastern European countries remain underrepresented. Poland and Lithuania each contribute 5 programmes, the Czech Republic 2, and Romania, Slovenia, and Serbia each appear with a single programme. This underrepresentation may partly reflect the search strategy's reliance on

English-language databases, but it also aligns with broader patterns of investment in sustainability higher education across the continent.

Outside Europe, the dataset includes 2 programmes from the United States and 1 from Singapore. Several Erasmus Mundus joint programmes appear under multiple country affiliations (e.g., Portugal–Germany–Netherlands, Spain–Netherlands–Portugal, Spain–Portugal–Italy–UK), demonstrating the European commitment to cross-border educational mobility and collaboration.

3.2. Programme Types and Structure

Master of Science (MSc) degrees dominate the offerings, representing approximately 90% of all programmes identified. This reflects the technical and quantitative nature of education at the AI-sustainability intersection, where competencies in data analysis, modelling, and computational methods are central to the curriculum. Master of Arts (MA) programmes account for 4% of offerings, typically emphasising policy, governance, or social dimensions of sustainability. Professional degrees appear less frequently: MBA and MEng programmes each represent 1.7%, with isolated offerings including MPhil, MRes, MSt, LLM, and AdvM degrees.

Programmes follow two dominant structural models. One-year intensive programmes (60 ECTS or 180 UK credits) are concentrated in UK institutions, delivering a compressed curriculum within three terms. These programmes assume prior technical or domain knowledge and offer limited time for foundational training, internships, or extended research projects. Two-year programmes (120 ECTS) align with the Bologna framework and characterise continental European offerings, accommodating extended projects, internships, and mobility components.

3.3. Thematic Classification of Programmes

The thematic classification reveals a concentration of sustainability education in business and policy domains rather than in technical or scientific fields.

Program Categories Distribution

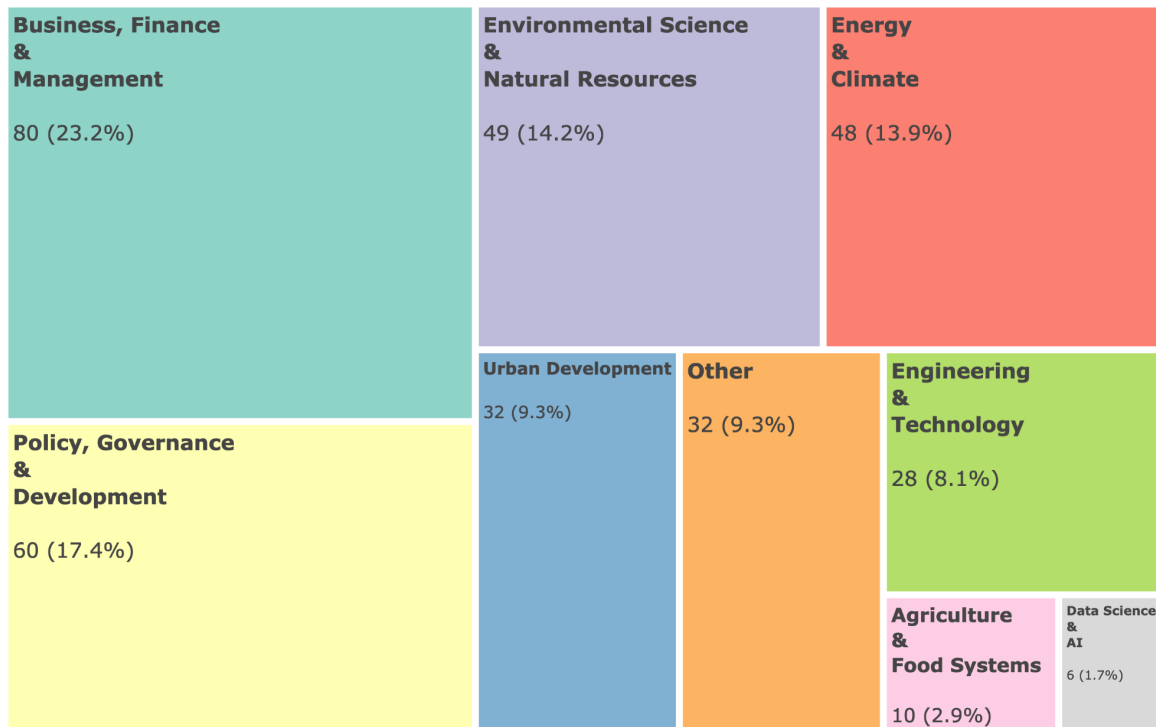


Figure 2: Thematic distribution of 345 sustainability-focused postgraduate programs across nine categories.

Business, Finance & Management programmes constitute the largest category with 80 programmes (23.2%), followed by Policy, Governance & Development with 60 programmes (17.4%). Together, these two categories account for over 40% of the total landscape, indicating that sustainability education predominantly frames the challenge through economic and governance lenses.

Environmental Science & Natural Resources programmes (49, 14.2%) and Energy & Climate programmes (48, 13.9%) together represent over a quarter of all programmes, reflecting traditional disciplinary strengths in sustainability research and education. Urban Development (32, 9.3%) and Engineering & Technology (28, 8.1%) show moderate representation.

At the lower end of the distribution, Agriculture & Food Systems accounts for only 10 programmes (2.9%), and Data Science & AI contributes just 6 programmes (1.7%). The minimal presence of dedicated Data Science & AI programmes within the sustainability education landscape is a significant finding: it confirms that the AI-sustainability intersection remains a niche rather than a mainstream educational offering, despite the growing recognition of AI's potential contributions to sustainability challenges. An additional 32 programmes (9.3%) were classified as "Other," encompassing interdisciplinary offerings that did not fit neatly into a single category.

3.4. AI Integration Across the Landscape

A central objective of this review was to assess the extent to which AI competencies are integrated into sustainability education. The findings show a wide gap between the importance attributed to AI for sustainability and the degree to which educational programmes equip learners with AI skills.



Figure 3: Distribution of AI integration levels across all 345 sustainability-focused programs.

Of the 345 programmes reviewed, only 9.0% (31 programmes) integrate AI as a mandatory, substantive component of the curriculum. An additional 19 programmes (5.5%) include AI peripherally, through optional modules or brief introductions within broader courses. The vast majority (85.5% of all programmes surveyed) contain no AI-related content whatsoever, focusing exclusively on sustainability domain knowledge.

3.4.1. AI Integration by Disciplinary Category

The degree of AI integration varies substantially across thematic categories, revealing clear disciplinary divides in computational readiness.

AI Integration by Category

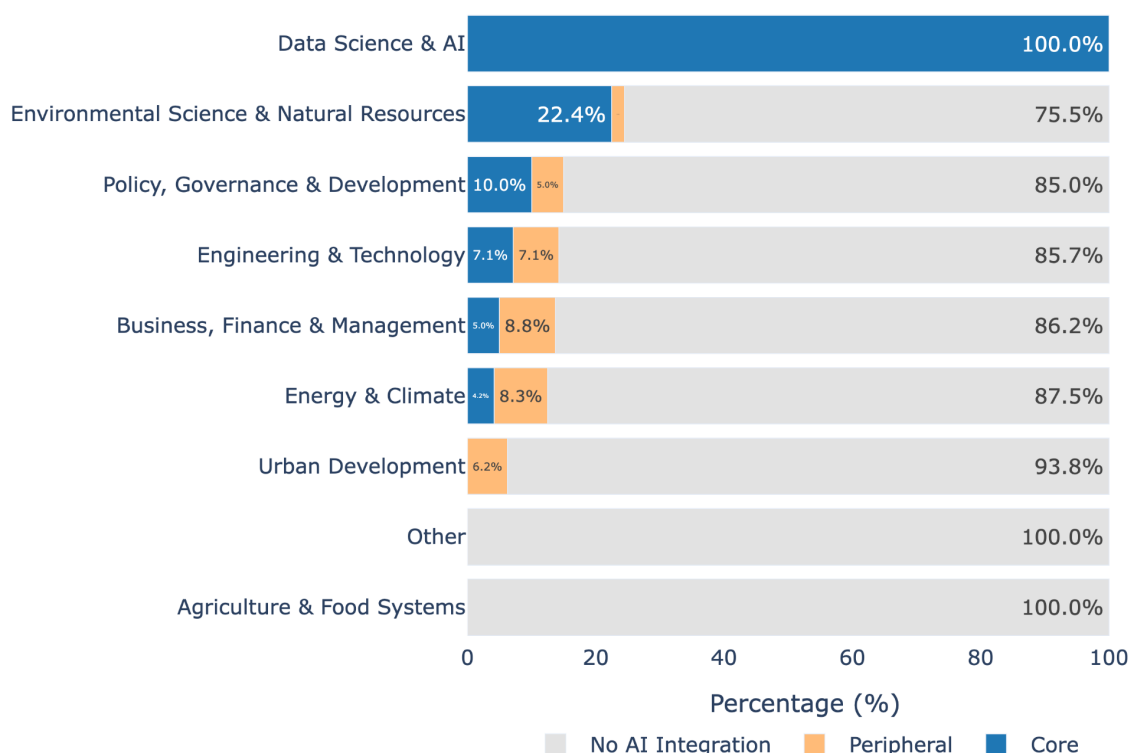


Figure 4: AI integration levels (Core, Peripheral, None) by program thematic category.

As expected, Data Science & AI programmes achieve 100% core integration. Among the broader sustainability domains, Environmental Science & Natural Resources programmes demonstrate the most meaningful integration, with 22.4% core and 2.1% peripheral AI content. This higher rate likely reflects the quantitative traditions of environmental science, where computational modelling, remote sensing, and data analysis have long been part of the research toolkit.

Policy, Governance & Development programmes show 10.0% core integration, suggesting that a small but growing number of programmes recognise the relevance of AI for governance and decision-making applications. Engineering & Technology programmes, despite their technical orientation, show a surprisingly low adoption rate (7.1% core, 7.1% peripheral).

Business, Finance & Management programmes, despite being the largest category by number, remain largely AI-free at the core level (5.0% core), though 8.8% include peripheral AI content, possibly reflecting the growing interest in AI for ESG reporting and corporate sustainability analytics. Energy & Climate programmes show a similar pattern (4.2% core, 8.3% peripheral).

Urban Development programmes show only peripheral integration (6.2% peripheral, no core), while Agriculture & Food Systems and the “Other” category show no AI integration at all.

A pattern is visible across the data: in four of the six categories where AI is neither the full focus nor completely absent, peripheral integration exceeds core integration. Sustainability programmes tend to treat AI as supplementary content, typically offered as an elective module or brief introduction, rather than as a fundamental methodology. This peripheral approach limits graduates’ ability to independently apply AI techniques to domain-specific sustainability problems.

3.5. Curricular Content and Pedagogical Orientation

To move beyond structural and categorical descriptors, a keyword-based analysis was conducted across all programmes with available course data (314 of 345) and across all programme descriptions (344 of 345). This analysis examines what concepts are taught and how programmes position themselves pedagogically, providing a landscape-level view of curricular priorities and instructional approaches.

3.5.1. Dominant Content Themes and Key Structural Components

A keyword scan of published course lists reveals a curriculum landscape firmly anchored in sustainability domain knowledge. Sustainability-related terms appear in nearly 80% of programmes, and domain-specific themes are well represented: energy and renewables (31.8%), modelling and simulation (29.3%), policy and governance (26.4%), climate and carbon (25.2%), and urban systems (17.8%). Structural components are also widespread, with thesis or dissertation work present in over half of all programmes (53.2%) and project or capstone modules in nearly half (49.0%). Research methods (18.8%) and internship or placement opportunities (20.4%) round out the picture of programmes that combine substantive domain knowledge with research training and professional experience.

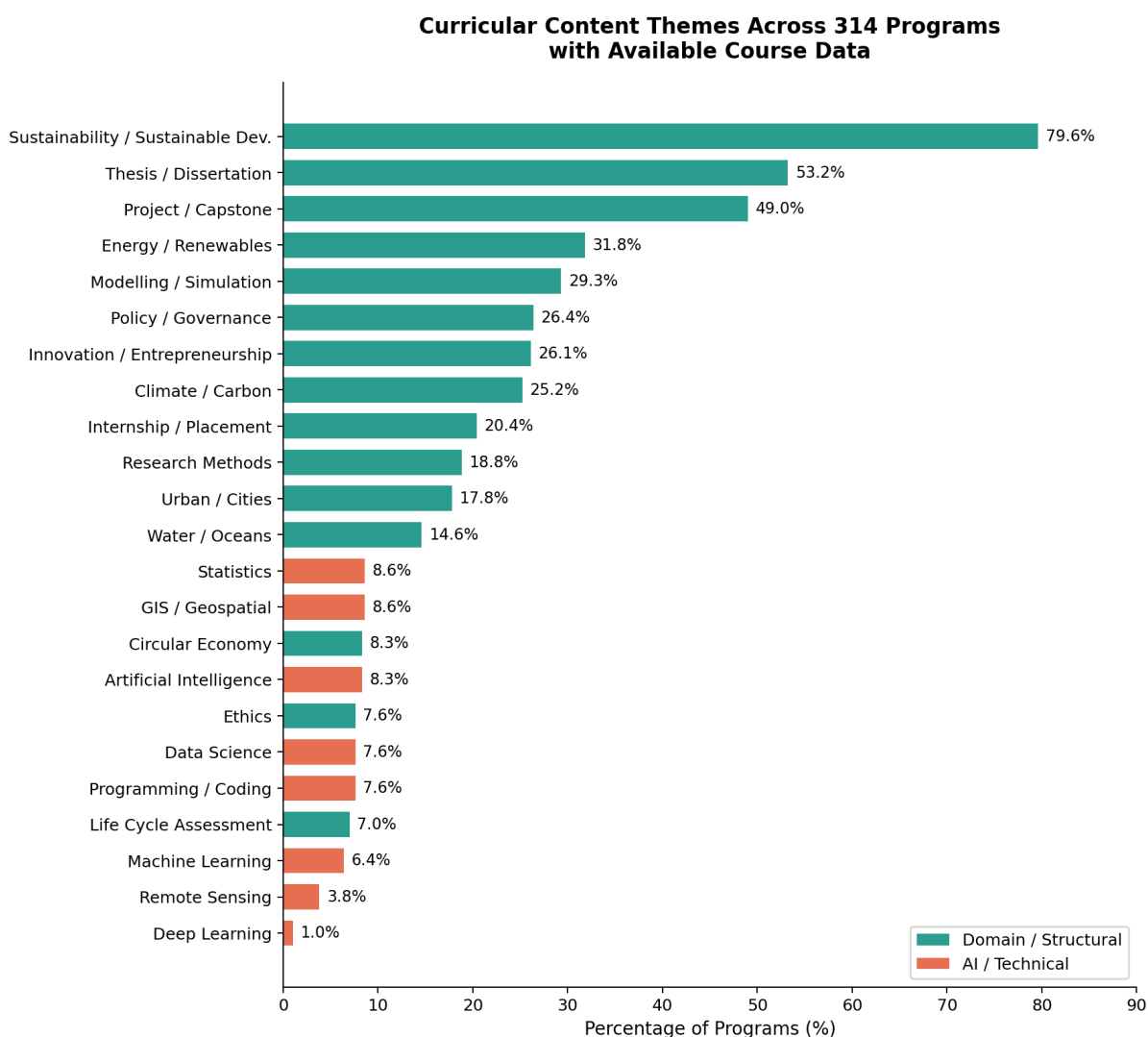


Figure 5: Frequency of curricular content themes across 314 programs with available course data. AI and technical themes (coral) are concentrated at the bottom of the distribution.

The contrast with AI and computational themes is striking. Artificial intelligence is mentioned in the course lists of only 8.3% of programmes, data science in 7.6%, machine learning in 6.4%, programming in 7.6%, and deep learning in just 1.0%. Even statistics, the most basic quantitative foundation, appears in only 8.6% of course lists. This pattern confirms that the AI integration gap identified in Section 3.4 is not a classification artefact: at the level of individual courses, AI and computational methods are genuinely absent from the vast majority of sustainability curricula.

Two additional findings merit attention. First, ethics appears in only 7.6% of course lists, suggesting that even ethical reasoning about technology and sustainability is not yet a mainstream curricular component. Second, life cycle assessment (7.0%) and circular economy (8.3%), despite their growing policy importance, remain niche topics rather than standard elements of sustainability education.

3.5.2. Pedagogical Orientation

Analysis of programme descriptions reveals how institutions frame and position their sustainability offerings. The most commonly emphasised orientations are international or global focus (44.5%), research orientation (37.2%), interdisciplinarity (30.2%), and industry or professional connections (29.9%). One in five programmes (20.1%) highlights practical or hands-on learning, and 12.8% explicitly mention collaborative learning.

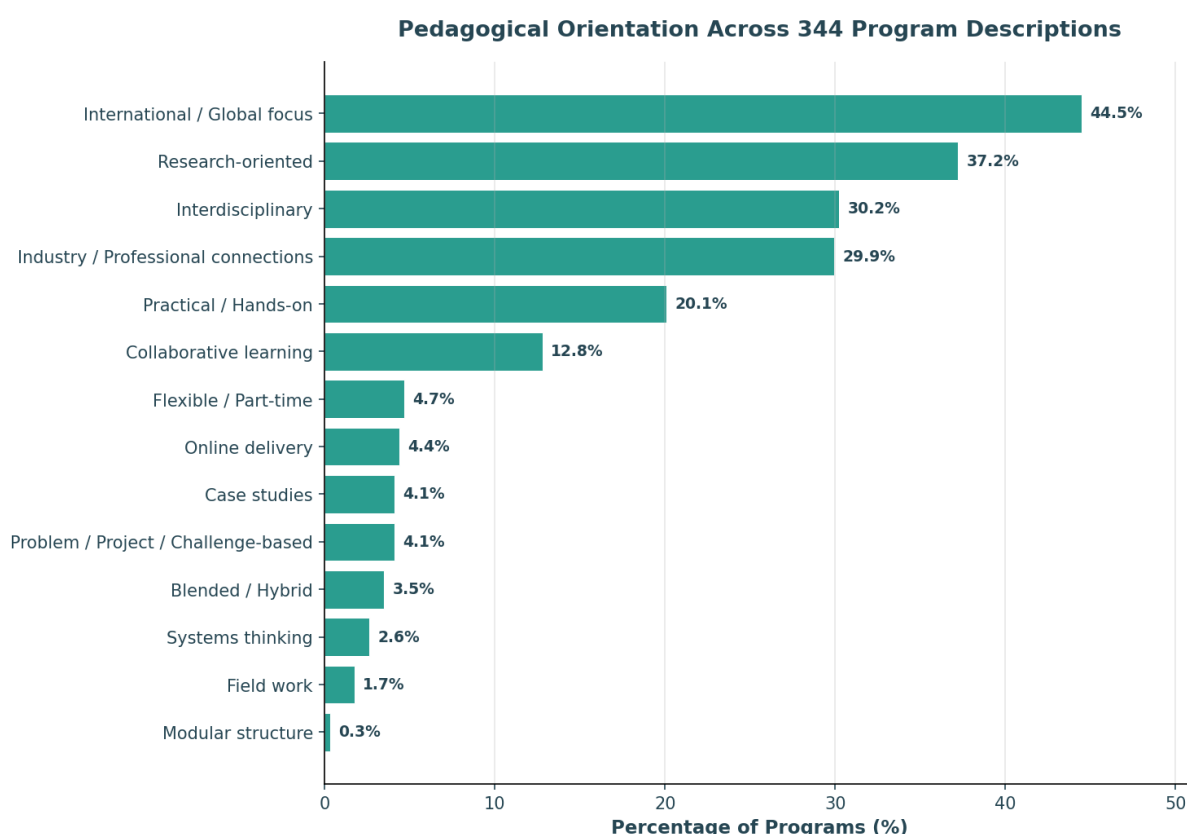


Figure 6: Percentage of programs emphasising each pedagogical approach in their published descriptions.

The lower end of the distribution is instructive. Flexible or part-time options are mentioned by fewer than 5% of programmes, and online delivery by only 4.4%. Blended or hybrid formats, despite their growing importance in post-pandemic higher education, appear in just 3.5% of programme descriptions. Problem-based, project-based, and challenge-based learning,

approaches widely regarded as effective for interdisciplinary competency development, are explicitly mentioned by only 4.1% of programmes.

The picture that emerges is of sustainability education that aspires to interdisciplinarity and global relevance but remains overwhelmingly campus-based, full-time, and structured around traditional academic delivery. The limited availability of flexible, modular, and digitally enabled learning pathways reinforces the rationale for micro-credential approaches that can reach learners who cannot commit to conventional degree structures.

3.6. Strengths and Weaknesses of the Current Landscape

3.6.1. Strengths

Breadth of sustainability coverage. The landscape reflects a mature and diversified sustainability education ecosystem. Programmes address a wide range of sustainability dimensions, from environmental science and climate action to business strategy and governance, providing learners with multiple entry points into the field.

Established structural frameworks. The prevalence of ECTS-denominated programmes within the Bologna framework provides a strong foundation for credit recognition and transferability across European institutions. This infrastructure is directly relevant to the design of stackable micro-credentials.

Strong quantitative traditions in environmental science. Environmental Science & Natural Resources programmes show the highest rates of AI integration among non-AI-specialist categories. This suggests that disciplinary traditions involving quantitative methods, modelling, and data analysis create a natural pathway for AI adoption.

Geographic reach and mobility. The presence of Erasmus Mundus joint programmes and the concentration of offerings across multiple European countries demonstrate a strong commitment to international collaboration and learner mobility in sustainability education.

3.6.2. Weaknesses

Critical AI skills deficit. The most significant finding of this review is the pervasive absence of AI integration in sustainability education. With 85.5% of programmes containing no AI content and only 9.0% integrating it at the core level, the vast majority of sustainability graduates enter the workforce without computational skills that are increasingly essential for evidence-based sustainability practice.

Disciplinary silos. AI integration follows disciplinary comfort with computational methods rather than problem domain need. The fields with the greatest potential demand for AI applications in sustainability (business, policy, urban development) are among the least likely to include AI in their curricula. This suggests that educational offerings are driven by existing faculty expertise rather than by the evolving needs of the sustainability profession.

Peripheral treatment of AI. Even where AI appears in sustainability programmes, it is more often treated as supplementary than foundational. Peripheral integration through optional modules or brief introductions does not equip learners to independently design, implement, or critically evaluate AI solutions for sustainability challenges.

Minimal dedicated AI-sustainability programmes. Only 6 programmes (1.7%) are specifically dedicated to Data Science & AI within a sustainability context. This confirms that the intersection

of these two fields has not yet crystallised as a recognised educational domain, despite clear professional demand.

4. Design Conventions and Standards

This section examines the common approaches and standards that institutions use to organise sustainability education. It draws on the full landscape of 345 programmes and provides detailed analysis of the 31 programmes identified as having core AI integration. The focus is on the institutional infrastructure—credit systems, delivery modes, assessment conventions, and admission standards—that any new educational offering must be compatible with.

The following sections present findings from the detailed analysis of the 31 core AI-integration programmes, with references back to the broader landscape where relevant.

4.1. Structural Standards and Credit Frameworks

The landscape review mapped the structural landscape across all 345 programmes. This section narrows the analysis to the 31 programmes with core AI integration, examining how structural and credit frameworks operate in programmes that have already navigated the challenge of combining computational and sustainability content.

4.1.1. *The European Credit Transfer and Accumulation System*

The dominant structural framework across the reviewed programmes is the European Credit Transfer and Accumulation System (ECTS), which is used by the vast majority of continental European institutions. ECTS provides a standardised measure of student workload, where one credit corresponds to approximately 25–30 hours of learning activity, including contact hours, self-study, and assessment. This framework is central to the Bologna Process and facilitates credit recognition, transfer, and accumulation across European higher education institutions.

Programmes aligned with the Bologna framework typically require 120 ECTS for a two-year master's degree, distributed across four semesters. This standard allows for substantial depth, including extended research projects, internships, and student mobility periods. The 120 ECTS structure also accommodates bridge modules that build baseline competencies for learners entering from diverse disciplinary backgrounds, a feature particularly relevant for programmes at the AI-sustainability intersection where learners may arrive with strong sustainability knowledge but limited computational skills, or vice versa.

4.1.2. *United Kingdom Credit Frameworks*

UK institutions operate under a distinct credit system. A standard one-year taught master's degree comprises 180 UK credits (equivalent to 90 ECTS), distributed across three terms. Some Scottish institutions use 240 Scottish credits for integrated master's programmes. The UK system produces a compressed curriculum that delivers equivalent qualification levels in a shorter timeframe, which has implications for both curriculum depth and learner workload.

The concentration of UK programmes in the broader dataset (62 of 345 programmes, 18%) carries over into the core subset, where 14 of 31 programmes (45%) are based in the UK. The UK approach assumes prior technical or domain knowledge at entry, leaving limited space for foundational modules or extended practical experiences such as internships.

4.1.3. *Structural Bifurcation and Its Implications*

The coexistence of these two models creates a clear structural bifurcation in the landscape.

Program Duration Distribution

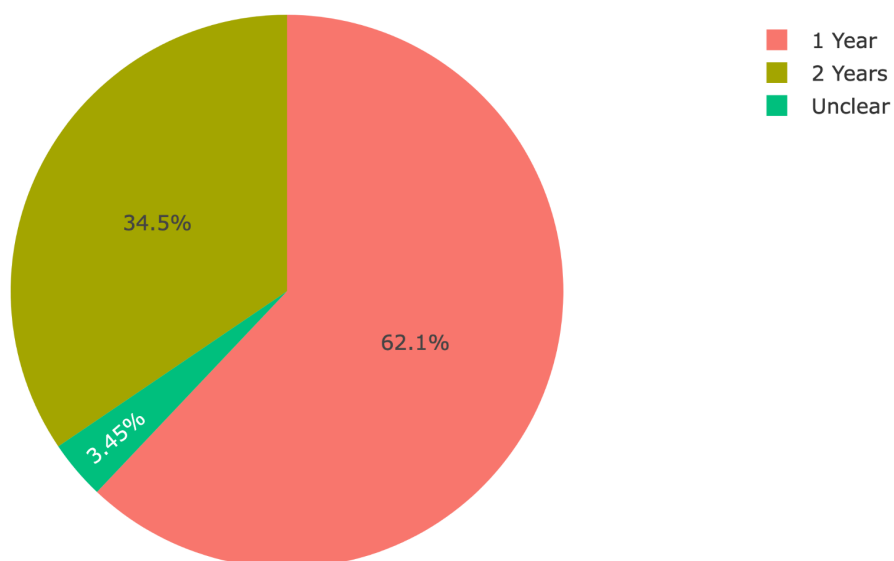


Figure 7: Distribution of programme duration across the 31 programmes with core AI integration, showing the dominance of one-year (58.1%) and two-year (41.9%) models.

Among the 31 programmes with core AI integration, 58.1% follow the one-year model and 41.9% follow the two-year model. The predominance of the one-year model in core AI-integration programmes reflects the UK's overrepresentation in this subset and suggests that institutions with established AI teaching capacity (often research-intensive UK universities) have been faster to create programmes at this intersection.

Neither model fully addresses the needs of lifelong learners. The two-year Bologna model offers depth but requires a substantial time commitment that is impractical for mid-career professionals. The one-year UK model reduces the time barrier but assumes prior preparation and still requires full-time enrolment in most cases. This gap supports the rationale for exploring more granular, flexible alternatives such as micro-credential frameworks.

4.2. Delivery Modes and Teaching Approaches

Analysis of the 31 programmes with core AI integration reveals a set of common delivery approaches, though the mix varies considerably across institutions.

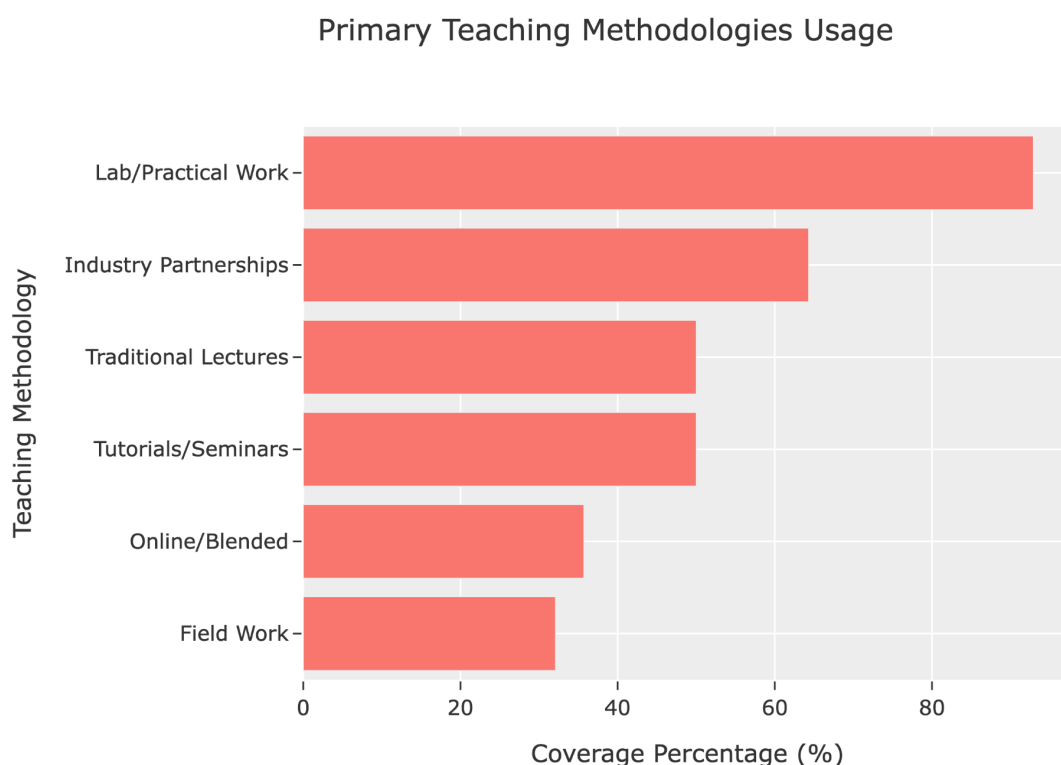


Figure 8: Coverage of primary teaching methodologies across the 31 programs with core AI integration.

4.2.1. Laboratory and Practical Work

The most prevalent delivery approach is laboratory and practical work, featured in 29 of 31 programmes (approximately 94%). This near-universal adoption reflects a recognition that AI competencies are fundamentally skill-based: learners must practice data manipulation, model implementation, and result interpretation through hands-on computing exercises. Practical sessions typically involve guided work with real or simulated datasets using programming environments such as Python, R, or specialised tools for geospatial analysis.

The dominance of practical work as a delivery mode signals a consensus across institutions that lecture-only formats are insufficient for developing AI competencies. The implication for micro-credential design is clear: any modular offering in this space must include a practical component, which in turn requires appropriate computational infrastructure and learner support.

4.2.2. Industry Partnerships and Real-World Engagement

Industry partnerships feature in 21 of 31 programmes (approximately 68%), connecting students to employers, data providers, and problem owners. These partnerships take various forms: guest lectures from practitioners, industry-sponsored capstone projects, access to proprietary datasets, and placement opportunities. The prevalence of industry engagement reflects the applied nature of AI-for-sustainability education, where relevance to professional practice is a key value proposition.

Programmes with strong industry ties tend to offer more current and practically relevant content, as partnerships create feedback loops between educational offerings and evolving professional

needs. However, the dependence on local or national industry networks means that the quality and relevance of these partnerships varies significantly across institutions and countries.

4.2.3. Tutorials and Seminars

Sixteen of 31 programmes (52%) use tutorials and seminars for small-group discussion, problem-solving, and individualised feedback. These formats complement larger lecture and lab sessions by providing spaces for deeper engagement with complex concepts, peer learning, and formative assessment. In programmes covering both AI techniques and sustainability applications, tutorials serve as important sites for interdisciplinary dialogue, where learners from different backgrounds can exchange perspectives.

4.2.4. Traditional Lectures

Traditional lectures appear as a primary delivery mode in only 14 of 31 programmes (approximately 45%). This relatively low figure reflects a broader pedagogical shift in higher education, with many programmes moving towards flipped classroom, active learning, or blended approaches where content delivery occurs asynchronously and contact time is reserved for interactive activities.

The declining centrality of lectures is particularly notable in technically-oriented programmes, where passive content consumption is poorly suited to developing the procedural knowledge required for AI implementation. Several programmes explicitly describe a blended model where theoretical foundations are delivered through online materials, while face-to-face sessions focus on guided practice and collaborative problem-solving.

4.2.5. Online and Blended Delivery

Twelve of 31 programmes (approximately 39%) offer online or blended delivery options. This proportion, while substantial, represents less than half of the programmes and indicates that on-campus delivery remains the dominant model for AI-sustainability education. The programmes offering blended delivery typically target working professionals, international students, and learners who cannot relocate, suggesting that flexibility in delivery is driven by learner demographics rather than pedagogical preference.

The limited adoption of blended learning is notable given the acceleration of online education technologies during and after the COVID-19 pandemic. It suggests that many institutions have returned to predominantly in-person formats, or that the practical and collaborative dimensions of AI education are perceived as difficult to replicate online.

4.2.6. Field Work

Ten of 31 programmes (approximately 32%) include field work components such as site visits, environmental sampling, and stakeholder engagement activities. Field work is concentrated in programmes with an environmental science focus, where direct observation of environmental systems and engagement with local stakeholders complement computational analysis. These components provide important contextual grounding for AI applications, ensuring that technical methods are informed by domain realities.

4.3. Assessment Approaches and Practices

Assessment practices across the 31 core AI-integration programmes emphasise practical demonstration of competencies, with a mix of individual and collaborative formats.

Assessment Methods Usage Across Programs

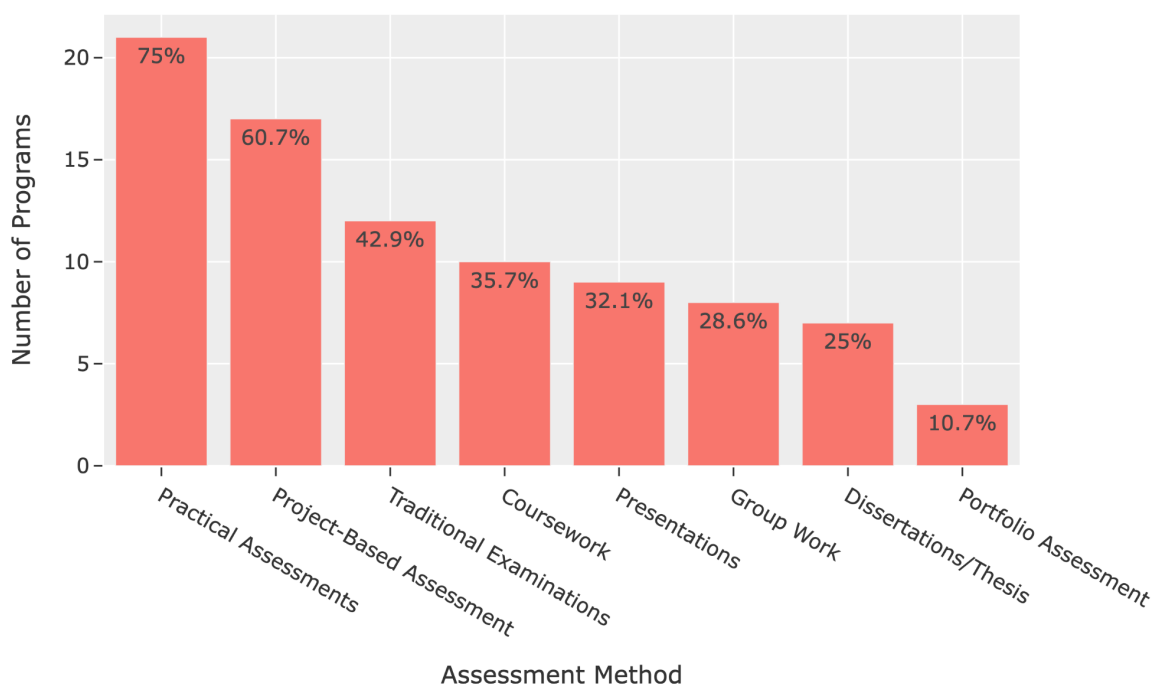


Figure 9: Assessment methods used across the 31 programs with core AI integration, showing the prevalence of practical assessments.

4.3.1. Practical Assessments

Practical assessments, including lab work, coding assignments, and hands-on data analysis exercises, are the most common assessment format, used in 23 of 31 programmes (74%). This dominance aligns with the emphasis on laboratory work in delivery modes and reflects an institutional consensus that AI competencies require demonstrated implementation ability, not only conceptual understanding.

Practical assessments typically involve tasks such as implementing a machine learning pipeline on a provided dataset, performing exploratory data analysis, or building and evaluating predictive models. These assessments directly measure the technical skills that employers expect and that the programmes aim to develop.

4.3.2. Project-Based Assessment

Nineteen of 31 programmes (61.3%) use project-based assessment through capstone projects, group consultancy exercises, or individual research projects. These assessments require learners to synthesise knowledge and skills acquired across multiple modules, applying them to a substantial, often open-ended problem. Project-based assessment is particularly valued in sustainability contexts, where real-world problems are complex, multi-stakeholder, and rarely reducible to a single technique.

Capstone projects frequently involve collaboration with external partners (industry, NGOs, or government agencies), providing learners with experience in translating between technical capabilities and stakeholder needs, a competency that is often cited as critical but rarely explicitly assessed.

4.3.3. Traditional Examinations

Thirteen of 31 programmes (41.9%) include traditional examinations, ranging from closed-book tests of foundational knowledge to open-book assessments of conceptual understanding and method selection. While examinations remain a common component, they are rarely the sole or primary assessment method, typically complementing practical and project-based formats.

4.3.4. Coursework and Written Assignments

Ten of 31 programmes (32.3%) use coursework such as essays, reports, and written assignments. These formats assess analytical writing, literature synthesis, and the ability to articulate technical findings for non-specialist audiences. In programmes bridging AI and sustainability, written assignments often require learners to contextualise technical results within broader sustainability frameworks.

4.3.5. Presentations

Ten programmes (32.3%) include presentations as a formal assessment component. Presentations develop and assess communication competencies essential for translating technical AI findings to diverse audiences, including policymakers, business leaders, and community stakeholders. This format recognises that the impact of AI in sustainability contexts depends not only on technical accuracy but also on the ability to communicate results persuasively and accessibly.

4.3.6. Group Work

Nine programmes (29.0%) formally assess group work through team projects, collaborative assignments, and peer evaluation. Collaborative assessment reflects the inherently interdisciplinary nature of AI-sustainability challenges, where effective solutions typically require input from specialists across multiple domains.

4.3.7. Dissertations and Theses

Eight programmes (25.8%) include dissertations or thesis components, concentrated in two-year or research-oriented programmes. These extended research projects allow learners to make original contributions to knowledge at the AI-sustainability intersection but require substantial time commitments that are difficult to accommodate in one-year or modular formats.

4.3.8. Gaps in Assessment Standards

While the assessment landscape shows diversity in format, a gap exists in the standardisation of interdisciplinary assessment. The majority of existing rubrics focus on either technical accuracy (code performance, model metrics) or traditional academic reflection (essay quality, literature engagement). Few programmes employ assessment frameworks that explicitly evaluate a learner's ability to select appropriate AI methods for specific sustainability problems, to critically interpret model outputs in domain context, or to navigate the ethical dimensions of deploying AI in high-stakes environmental or social settings. This absence of competency-based, interdisciplinary assessment standards represents both a weakness of the current landscape and an opportunity for innovation.

4.4. Admission Standards and Entry Pathways

The admission standards observed across the 31 core AI-integration programmes reveal distinct approaches to managing the interdisciplinary challenge of bringing together learners from diverse backgrounds.

4.4.1. Entry Requirements by Programme Structure

One-year programmes, predominantly in the UK, generally assume prior technical or domain knowledge at entry. The compressed timeline leaves limited space for foundational modules, meaning that learners are expected to arrive with either strong computational skills (if the programme emphasises sustainability applications) or strong domain knowledge (if the programme builds technical skills on top of sustainability understanding). Formal prerequisites typically include a bachelor's degree in a relevant field, though the definition of “relevant” varies across institutions.

Two-year programmes, aligned with the Bologna framework, accommodate more diverse entry profiles. The extended timeline allows for bridge modules in the first semesters that build baseline competencies, whether in programming and statistics (for domain experts entering the field) or in sustainability concepts and systems thinking (for technically trained learners). This structural flexibility makes two-year programmes more accessible to career changers and professionals from non-traditional backgrounds.

4.4.2. Industry Experience and Alternative Pathways

Twenty-one of the 31 programmes maintain industry partnerships that suggest openness to applicants with substantial professional experience in lieu of formal academic prerequisites. However, the available programme documentation does not formally describe alternative entry pathways, prior learning recognition mechanisms, or prerequisite waiver processes. This lack of transparency makes it difficult for prospective learners, particularly mid-career professionals, to assess their eligibility without direct contact with programme administrators.

4.4.3. The Unanswered Directionality Question

A fundamental question that the available data cannot fully resolve is the directionality of interdisciplinary training in these programmes: do they primarily admit domain experts (sustainability professionals, environmental scientists) and provide AI training, or do they admit technical specialists (data scientists, computer scientists) and provide sustainability context? The answer likely varies across programmes, but the absence of clear documentation on this point represents a weakness in current programme design. Learners and employers benefit from transparency about what background a programme assumes and what competencies it builds.

4.5. Summary of Common Approaches

The following table synthesises the common approaches and standards identified across the reviewed programmes:

Design Dimension	Dominant Approach	Prevalence	Alternative Approaches
Credit framework	ECTS (Bologna)	Majority of continental European programmes	UK credits (180/240); US credit hours
Programme duration	One-year intensive	58.1% of core AI programmes	Two-year (41.9%) Bologna
Primary delivery	Lab/practical work	94% of core AI programmes	Blended learning (39%); lectures (45%)

Design Dimension	Dominant Approach	Prevalence	Alternative Approaches
Industry engagement	Partnerships	68% of core AI programmes	Field work (32%); guest lectures
Primary assessment	Practical assignments	74% of core AI programmes	Project-based (61.3%); exams (41.9%)
Entry pathway	Bachelor's in relevant field	Standard across all programmes	Professional experience (informal)
Interdisciplinary assessment	Not standardised	Limited adoption	Competency-based rubrics (emerging)

These standards provide a foundation for understanding the institutional infrastructure within which any new educational offering must operate. The next section turns from how programmes are structured to what they teach, examining the content and framework suitability for the specific demands of AI-sustainability education.

5. Content Analysis, Gap Analysis, and Framework Assessment

This section integrates three complementary analytical threads: examination of the content of the 31 programmes with core AI integration; identification of systematic gaps in curriculum coverage; and evaluation of the suitability of existing European micro-credential frameworks for AI-sustainability education.

5.1. Content Analysis of Programmes with Core AI Integration

The 31 programs with core AI integration were subjected to detailed individual examination as described in the methodology (Section 2). For each program, a researcher visited the institution's official website and systematically extracted all publicly available curriculum information, including program descriptions, module-level syllabi, stated learning objectives, teaching methodologies, assessment methods, and expected outcomes.

This section examines the 31 programs identified as having core AI integration. These programs span universities in the United Kingdom, Austria, Germany, Ireland, Italy, Portugal, Singapore, and the United States, with credit requirements between 60 and 120 ECTS depending on national frameworks.

Program Distribution by Country

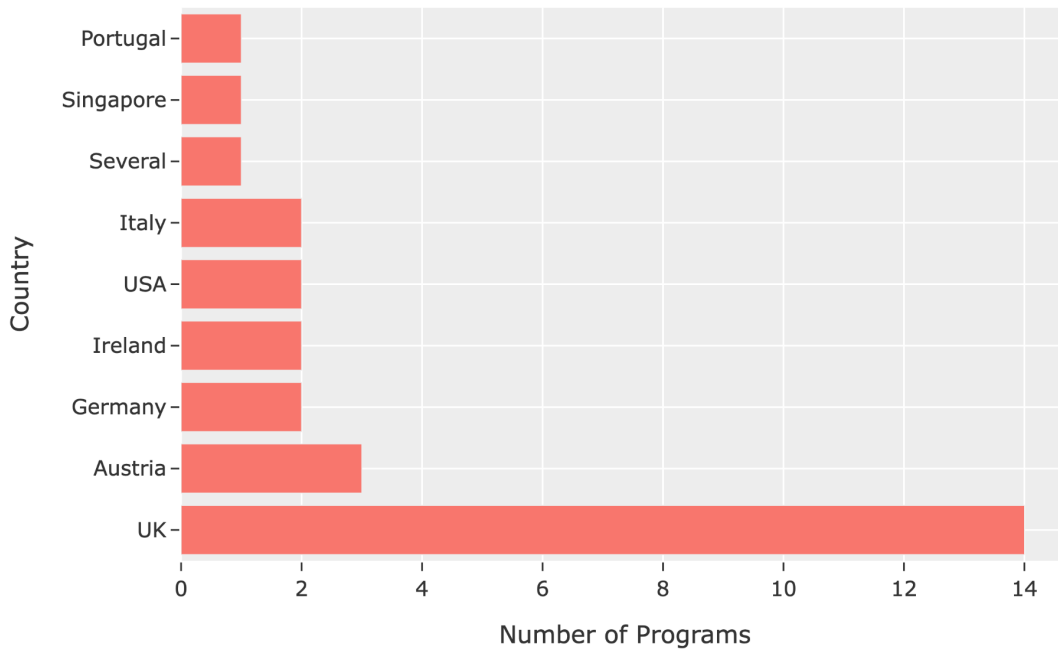


Figure 10: Distribution of the 31 core AI-integration programs by country.

The concentration of core AI programs in the United Kingdom (14 of 31) confirms the trend identified in the landscape review (Section 3): English-language institutions with established AI research capacity have been faster to create programs at this intersection.

5.1.1. Sustainable Development Goals Alignment

Programs were analysed for their alignment with the United Nations Sustainable Development Goals (SDGs) based on curriculum content and stated learning objectives.

SDG Frequency Across Programs

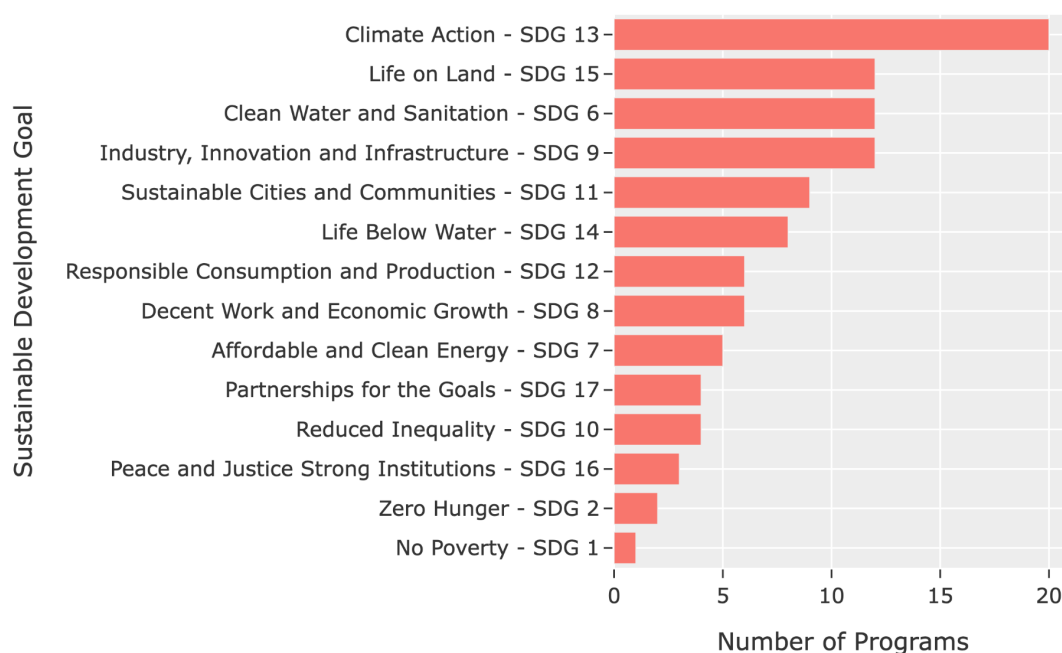


Figure 11: Frequency of SDG alignment across the 31 programs with core AI integration.

Climate Action (SDG 13) appears in 25 of 31 programs, establishing it as the dominant sustainability priority in AI-integrated education. Clean Water and Sanitation (SDG 6) and Life on Land (SDG 15) each feature in 18 programs, driven by curricula emphasising environmental monitoring, ecosystem modelling, and conservation applications. Industry, Innovation and Infrastructure (SDG 9) connects to 19 programs through technical AI components and their application to industrial transformation.

Life Below Water (SDG 14) appears in 11 programs, concentrated among institutions with coastal or marine research strengths. Affordable and Clean Energy (SDG 7) and Responsible Consumption and Production (SDG 12) each feature in 9–11 programs, reflecting energy systems and circular economy themes. Sustainable Cities and Communities (SDG 11) appears in 10 programs addressing urban analytics.

Underrepresented are goals related to social equity and human development: No Poverty (SDG 1), Zero Hunger (SDG 2), and Good Health and Well-being (SDG 3) together appear in fewer than 5 programs. Peace, Justice and Strong Institutions (SDG 16) features in 3 programs, and Partnerships for the Goals (SDG 17) in 6. This distribution reveals a curriculum emphasis on environmental and climate applications at the expense of social equity, food security, health informatics, and governance dimensions, which is a limitation given the interconnected nature of the SDG framework.

5.1.2. AI Techniques and Methods

Programs were analysed for the specific AI techniques and methods included in their curricula.

AI Techniques Coverage Across Programs

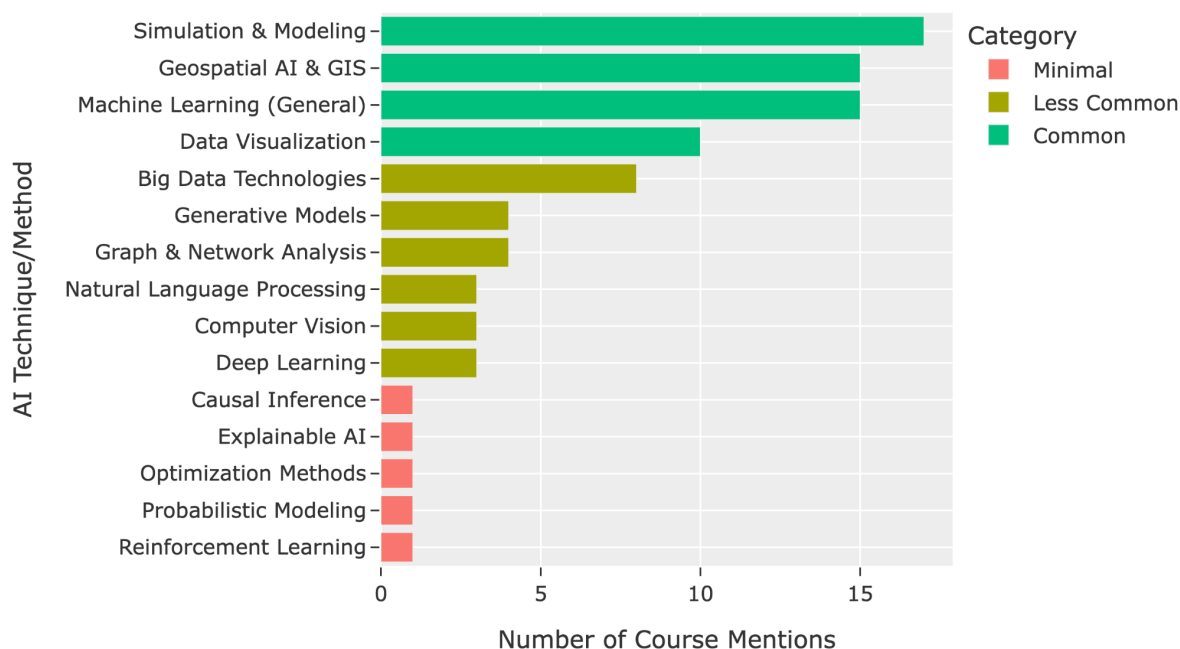


Figure 12: Coverage of AI techniques across the 31 programs, categorised by prevalence.

Common techniques. Simulation and modelling methods appear most frequently, with 19 course mentions across 13 programs, reflecting the importance of environmental system modelling and scenario analysis. Machine learning courses appear in 17 modules across 15 programs, indicating near-universal coverage of supervised learning fundamentals. Geospatial AI and geographic information systems receive substantial attention (17 modules across 11 programs), reflecting the spatial nature of environmental data and the centrality of remote sensing. Data visualisation and dashboard development feature in 11 modules across 11 programs.

Less common techniques. Big data technologies including distributed systems and cloud computing appear in 8 modules across 6 programs, representing less than half the corpus. Graph and network analysis features in 4 modules across 4 programs. Generative models appear in 4 modules, deep learning in only 3, computer vision in 3 modules across 2 programs, and natural language processing in 3 modules across 3 programs.

Minimally covered techniques. Reinforcement learning, probabilistic modelling, optimisation, explainable AI, and causal inference each appear in only one program. This minimal coverage is significant because several of these techniques have direct relevance to sustainability applications where decisions must be made under uncertainty, competing objectives must be balanced, and model transparency is required for stakeholder trust.

5.1.3. Learning Outcomes

All 31 programs emphasise technical AI competencies and real-world application as core outcomes. Twenty-eight programs explicitly focus their outcomes on sustainability priorities or SDG contributions.

Learning Outcomes Coverage Across Programs

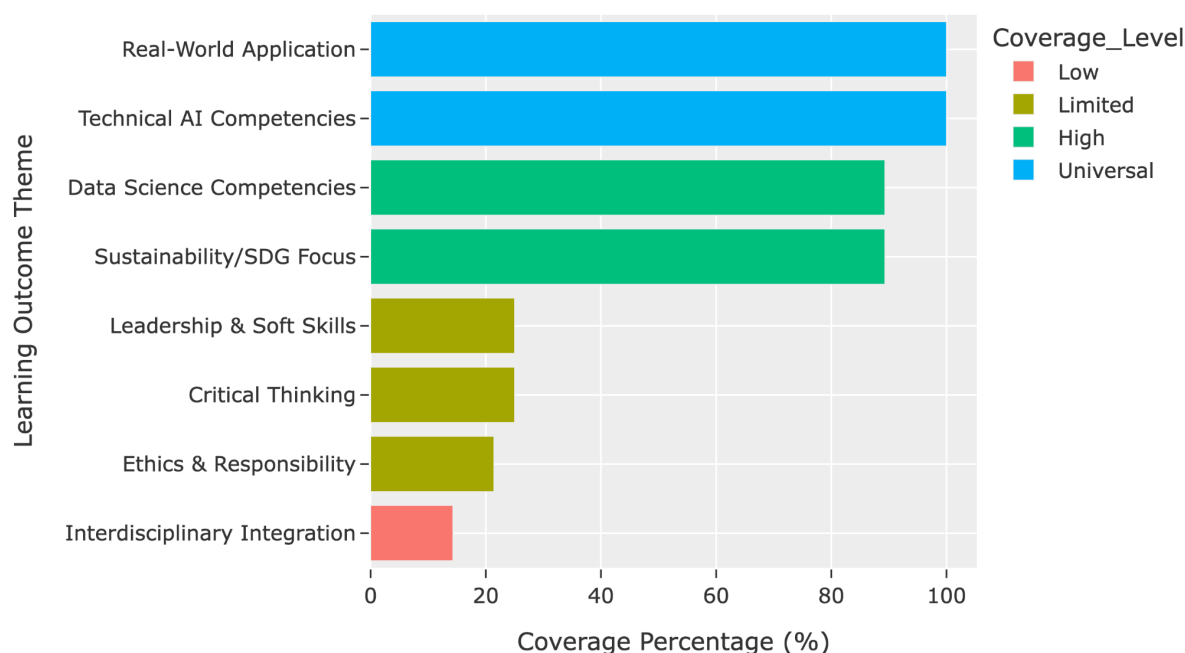


Figure 13: Coverage of learning outcome themes across the 31 core programs.

Data science competencies (data acquisition, preprocessing, analysis, interpretation) appear in 31 programs, reflecting how central data work is to sustainability applications. Technical AI competencies and real-world application are near-universal.

However, several important outcome dimensions are underrepresented. Only 8 programs emphasise critical thinking, analytical reasoning, and evaluation, suggesting that programs prioritise teaching techniques over helping students assess when methods are appropriate and what their limitations are. Leadership and soft skills appear in only 8 programs despite strong employer demand. Ethics, responsibility, and accountability feature in only 7 programs, indicating that the moral and social dimensions of deploying AI in high-stakes environmental contexts receive limited formal attention.

Only 4 programs treat interdisciplinary integration as a distinct learning outcome, exposing a gap between how programs describe interdisciplinarity in their marketing and whether they actually teach students to bridge technical and domain knowledge as a skill requiring dedicated practice and assessment.

The pattern that emerges is one of programs that teach AI techniques and sustainability topics in parallel but rarely cultivate the capacity to critically interpret AI results within sustainability contexts: to assess whether a model's output is meaningful, to identify its limitations in a specific decision-making scenario, or to communicate findings to stakeholders who lack technical backgrounds. These integrative competencies, which sit between technical proficiency and domain expertise, are the ones that a micro-credential program targeting the AI-sustainability intersection would need to prioritise.

5.2. Gap Analysis

The content analysis reveals substantial gaps in coverage of advanced AI methods relevant to sustainability applications. Research on AI's role in sustainable development has identified a wide range of techniques, from optimisation and predictive modelling to interpretability and uncertainty quantification, as essential for addressing interconnected environmental challenges (Vinuesa et al., 2020; Rolnick et al., 2022). The gaps identified below are assessed against both this broader research landscape and the specific demands of sustainability practice. They cluster around five capability areas.

Gap Analysis: Coverage Percentage by Capability Area

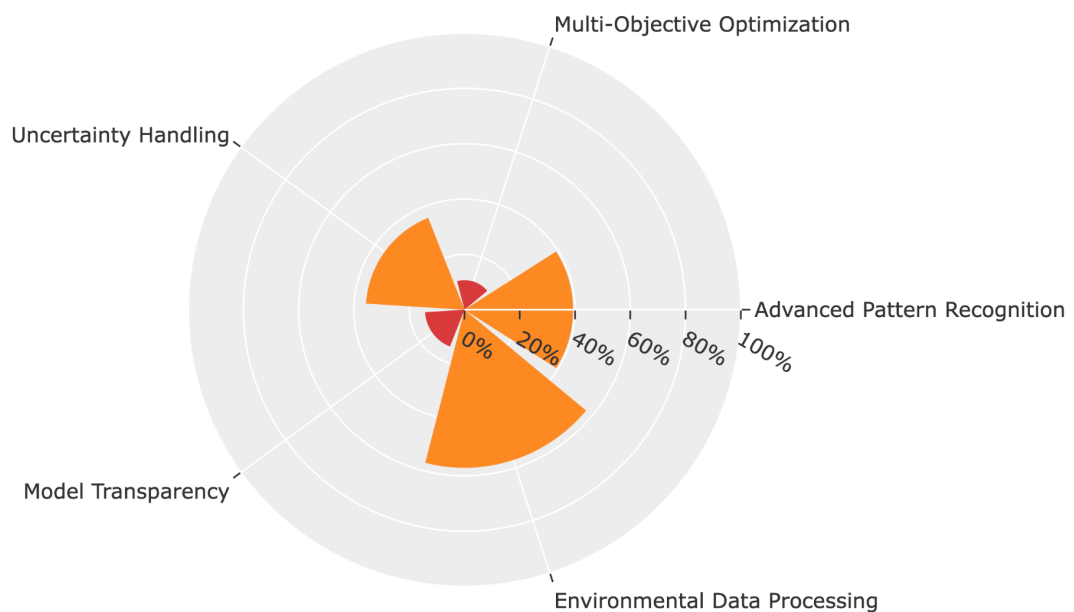


Figure 14: Radar chart showing the coverage percentage of five key capability areas across the 31 core programs.

5.2.1. Advanced Pattern Recognition in Complex Data

Twelve programs provide pattern recognition training, but they minimally cover methods for complex, interconnected, or sequential data. Methods for analysing networks and connections (essential for infrastructure networks, ecological food webs, and supply chains) receive no dedicated coverage. Methods for analysing patterns across time, despite their relevance to climate data and long-term environmental monitoring, are similarly absent. Techniques for combining different data types (e.g., integrating satellite imagery with ground sensor data, or combining textual reports with numerical measurements) are largely missing from curricula.

5.2.2. Optimisation Under Multiple Competing Objectives

Sustainability challenges inherently involve trade-offs between competing objectives: environmental protection versus economic development, species conservation versus human livelihoods, renewable energy versus land use. Yet only 3 of 31 programs address multi-objective optimisation. Evolutionary and swarm-based approaches, effective for resource allocation and

facility location under constraints, receive no coverage. Constrained optimisation receives minimal attention despite its relevance to energy system design, transportation planning, and resource scheduling.

5.2.3. Handling Uncertainty and Non-Stationarity

Environmental systems exhibit fundamental uncertainty from incomplete knowledge, measurement error, and inherent variability. Climate change introduces non-stationarity where historical patterns no longer predict future conditions. Eleven of 31 programs cover uncertainty handling, primarily through probabilistic modelling and statistical methods. However, frameworks for expressing prediction confidence, distinguishing uncertainty sources, and propagating uncertainty through model chains are largely absent. Methods for robust learning under distributional changes, critical when models trained on historical data must perform under novel climate conditions, receive limited attention. Ensemble methods that combine predictions from multiple models also lack coverage despite their effectiveness in environmental forecasting.

5.2.4. Model Transparency and Accountability

AI systems increasingly inform high-stakes environmental decisions, and both stakeholders and regulatory frameworks demand transparency. Yet only one program covers interpretability methods. Techniques to identify influential features, visualise model reasoning, or generate human-understandable explanations receive minimal attention despite their necessity for stakeholder trust and regulatory compliance. Sensitivity analysis, what-if scenario testing, and methods for understanding model behaviour under different conditions are absent despite their importance for communicating results to non-technical audiences.

5.2.5. Specialised Environmental Data Processing

While programs include general remote sensing, they minimally cover satellite image preprocessing, atmospheric correction, change detection, and multi-sensor fusion. Common statistical methods also receive minimal coverage: dimensionality reduction, clustering for ecosystem classification or pollution source identification, and time series forecasting all remain underrepresented despite pervasive need in environmental applications.

5.2.6. Implications for Curriculum Design

Taken together, the content gaps (Sections 5.2.1–5.2.5) and the learning outcome gaps identified in Section 5.1.3 suggest that existing programs fall short at multiple levels of knowledge maturity. At the foundational level, sustainability students lack basic AI literacy while AI students lack sustainability context, the mutual gaps that prevent meaningful interdisciplinary engagement. At the advanced level, programs that do teach AI techniques rarely cultivate critical thinking about when and how those techniques should be applied, the capacity to interpret AI results in domain-specific contexts, or the ability to evaluate model outputs against real-world constraints. At the domain-specific level, the advanced techniques most relevant to sustainability applications (multi-objective optimisation, uncertainty handling, model transparency) are the ones most consistently absent from curricula.

This layered pattern of gaps, from basic literacy through advanced interpretation to domain-specific application, points toward a curriculum architecture that addresses each level in sequence, building from foundational competence toward increasingly specialised and integrative capabilities. Critically, the evidence suggests that the differences between learner profiles may be most pronounced at the foundational level (where technical and non-technical learners need different entry points) and progressively narrower at advanced and domain-

specific levels, where all profiles converge on the shared challenge of applying AI responsibly and effectively to sustainability problems.

5.3. Assessment of Existing Micro-Credential Frameworks

This section evaluates whether the micro-credential frameworks currently available in Europe provide a suitable foundation for designing courses at the AI-sustainability intersection. The assessment draws on EU policy recommendations, operational guidelines, data interoperability standards, and emerging industry frameworks.

5.3.1. EU Council Recommendation on Micro-Credentials

The Council of the European Union's recommendation of 16 June 2022 defines a micro-credential as the record of learning outcomes acquired following a small volume of learning, assessed against transparent and clearly defined criteria. The recommendation identifies three core characteristics: limited length with careful assessment, relevance to societal and labour market needs, and portability combined with stackability.

These characteristics are supported by ten key principles: quality, transparency, relevance, valid assessment, learning pathway support, recognition, portability, learner-centredness, authenticity, and information and guidance. The recommendation also specifies minimum information requirements for micro-credential documentation, including learner identification, title, awarding body, learning outcomes, notional workload in ECTS, EQF level, assessment type, and form of participation.

Suitability assessment: The EU framework provides a strong policy foundation. Its emphasis on transparency, portability, and stackability aligns well with the RADAR-aim vision of modular credentials that learners can accumulate progressively. However, the framework is deliberately generic and does not address the specific challenges of interdisciplinary fields where competence boundaries are blurred, or of rapidly evolving technical domains where learning outcomes require frequent updating.

5.3.2. European Training Foundation Operational Guidelines

The ETF guidelines operationalise the EU recommendation across seven pillars: quality assurance as the foundation of trust, transparency and comparability, digital portability and interoperability, relevance to learners and labour markets, valid and reliable assessment, flexible learning pathways and stackability, and learner-centred and inclusive design.

The guidelines recommend embedding micro-credentials within existing institutional quality assurance systems, using risk-based approaches proportionate to the scope of the credential. They emphasise employer collaboration through co-design, endorsement, and integration into professional development schemes.

Suitability assessment: The ETF guidelines add practical depth to the EU policy framework, particularly regarding quality assurance proportionality and employer engagement. For AI and sustainability courses, the emphasis on employer collaboration is especially relevant, as the labour market for these interdisciplinary skills is still emerging and lacks established professional standards. The risk-based quality assurance approach is well-suited to micro-credentials that need to be updated frequently in response to technological change.

5.3.3. Emerging Industry Standards

Several industry-driven frameworks have emerged alongside EU policy. The Common Microcredentials Framework (CMF), proposed by the European Association of Distance Teaching

Universities (EADTU) and involving major European MOOC platforms (FutureLearn, FUN, MiriadaX, EduOpen, OpenupEd), specifies micro-credentials of 100–150 hours (4–6 ECTS), targeted at EQF levels 6–7, with clear assessment enabling academic credit. The QAA (UK Quality Assurance Agency) guide provides practitioner-focused guidance on learner access, curriculum design, assessment proportionality, and industry collaboration. The CIMEA (Italian Information Centre on Academic Mobility and Equivalence) framework emphasises methodological clarity, alignment with qualifications frameworks, and recognition of non-formal and informal learning.

Suitability assessment: These industry frameworks converge on workload ranges (4–6 ECTS), level targeting (EQF 6–7), and the centrality of assessment. The CMF’s alignment with ECTS and EQF provides a practical template for credential specification. However, none of these frameworks specifically address the challenges of interdisciplinary AI-sustainability content, such as how to assess competencies that span technical implementation and domain-specific critical thinking.

5.3.4. Fitness of Frameworks for AI and Sustainability

Micro-credential courses on AI and sustainability present three characteristics that test the boundaries of existing frameworks.

Interdisciplinary competences. The competences targeted by AI-sustainability courses are fundamentally interdisciplinary: systems thinking applied to AI-environment interactions, problem framing that bridges computational and domain perspectives, and assessment of long-term and unintended impacts of AI systems on society and the environment. Existing frameworks accommodate discipline-specific credentials well but offer limited guidance on how to structure, assess, and quality-assure competences that span disciplinary boundaries.

Responsiveness to rapid change. AI evolves rapidly, demanding frequent content updates at a pace that is challenging for traditional degree curricula. Micro-credential formats are inherently more adaptable than full degree programs, as individual modules can be updated independently. Existing QA instruments (EQF, ESG, EQAVET) can be linked to micro-credentials while maintaining flexibility beyond what traditional degrees allow.

Stakeholder alignment. Three key stakeholder groups have distinct but compatible needs: students seek focused skills aligned with rapidly changing labour market demand; higher education institutions seek to diversify offerings through smaller learning units; and employers seek transparent skill identification for recruitment and targeted training. Existing frameworks support these needs in principle, but operationalising them requires specific design choices around learning pathways, assessment types, and recognition mechanisms that the generic frameworks leave open.

5.3.5. Comparative Suitability Summary

Table 1 summarises the suitability of each framework across five criteria derived from the specific requirements of AI-sustainability micro-credential design: credit and level specification (capacity to denominate credentials in ECTS and classify by EQF level), quality assurance (provision of proportionate QA mechanisms), digital portability (support for verifiable, interoperable digital credentials), interdisciplinary accommodation (guidance on structuring competences that span disciplinary boundaries), and content update (mechanisms to support rapid updating of learning outcomes in response to technological change).

Ratings reflect the degree to which each framework addresses the criterion as assessed in Sections 5.3.1–5.3.3: Strong indicates comprehensive, operationally ready support; Moderate

indicates partial coverage or support in principle that requires adaptation; Limited indicates minimal or no explicit treatment.

Framework	Credit & Level Specification	Quality Assurance	Digital Portability	Interdisciplinary Accommodation	Content Update
ETF Operational Guidelines (2023)	Strong	Strong	Moderate	Limited	Moderate
CMF / EADTU	Strong	Moderate	Moderate	Limited	Moderate
QAA Characteristics Statement	Moderate	Strong	Limited	Moderate	Moderate
CIMEA Methodology	Moderate	Moderate	Moderate	Limited	Limited

6. Design Recommendations

The recommendations presented here follow a backward-design approach: defining learning outcomes based on identified gaps and stakeholder needs, then specifying assessment strategies aligned with those outcomes, and finally addressing course structure, learning environment, and quality assurance. This approach is especially suited to micro-credentials, which are short and focused, ensuring that every teaching activity aligns with intended goals and no essential content is missed.

6.1. Identify Learning Outcomes Aligned with Participant Backgrounds

The gap analysis in the the content and framework analysis (Section 5) revealed that existing programs fail to differentiate learning outcomes by learner profile, despite serving students from vastly different disciplinary backgrounds. The RADAR-aim micro-credential design should ground its outcomes in the competencies and skills learners should be able to demonstrate, differentiated by four distinct pathways:

Pathway 1: Data Science and AI Students. These learners bring strong technical backgrounds in AI, data science, computer science, or information technology. For them, micro-credential courses should build on existing AI expertise and orient it toward sustainability challenges. Learning outcomes should emphasise the application of advanced AI techniques (identified as gaps in the *Framework Suitability Assessment* (Section 5): multi-objective optimisation, uncertainty handling, model transparency) to sustainability-specific datasets and problems.

Pathway 2: Engineering and Design Students. These learners bring backgrounds in engineering, architecture, planning, modelling, or design, often already operating in sustainability-oriented contexts. For them, AI functions as a supporting tool rather than a development focus. Learning outcomes should emphasise the ability to specify AI requirements for domain problems, critically evaluate AI outputs, and integrate computational results into design and planning workflows.

Pathway 3: Social Sciences Students. These learners bring backgrounds in management, law, economics, humanities, or related fields. For them, engagement with AI is non-technical. Learning outcomes should emphasise AI literacy (understanding capabilities and limitations), ethical and governance dimensions of AI deployment in sustainability contexts, and the ability to commission, interpret, and critically evaluate AI-informed analyses.

Pathway 4: Working Professionals. These participants are already employed in organisations engaged in sustainability-oriented activities and seek to use AI strategically. Learning outcomes should adapt the three student pathways with a greater focus on organisational implementation, responsible AI adoption, and alignment with sustainability strategies such as ESG reporting.

This four-pathway structure is the RADAR-aim project’s response to what Section 4.4.3 identified as the “unanswered directionality question” in existing programs: do they primarily admit domain experts and teach them AI, or admit technical specialists and teach them sustainability? Existing programs leave this question unresolved, creating ambiguity for learners and employers. The pathway model resolves it by design: rather than choosing a single direction, the program explicitly accommodates both trajectories (and two further profiles), with learning outcomes calibrated to what each group needs to develop rather than what they already know.

Learning outcome development should be carried out in collaboration with industries and professional associations. These partnerships provide guidance on the knowledge, skills, and abilities that are relevant to the current labour market and signal the practical value of micro-credentials to prospective learners.

6.2. Develop an Assessment Strategy Aligned with Targeted Competences

The the content and framework analysis (Section 5) identified a gap in interdisciplinary assessment: existing programs assess either technical accuracy or traditional academic reflection, but rarely evaluate the ability to select appropriate AI methods for sustainability problems, critically interpret outputs in domain context, or navigate ethical dimensions of deployment.

The RADAR-aim assessment strategy should incorporate two complementary layers:

Frequent formative assessments provide instructors with confirmation of whether learners are progressing on challenging interdisciplinary topics and allow timely adjustment of materials and support. In AI-sustainability education, where topics cross disciplinary boundaries and challenge existing assumptions, formative assessment also stimulates learner self-reflection on the societal implications of what they are learning.

Meaningful final summative assessments should be authentic, measuring the learner’s performance in the context where they will apply the skills being assessed. Authentic assessments for AI-sustainability micro-credentials may include project work on real sustainability datasets, case study analysis requiring method selection and critical interpretation, video presentations demonstrating the ability to communicate technical findings to non-technical audiences, simulations requiring decision-making under uncertainty, or portfolio-based evidence of applied competence. The emphasis on authentic assessment responds directly to the finding in the design conventions analysis (Section 4) that 75% of existing programs already use practical assessments, while addressing the identified weakness in interdisciplinary and ethical evaluation.

6.3. Define Inclusive Course Structures

the design conventions analysis (Section 4) identified that only 39% of existing programs with core AI integration offer blended delivery, and the landscape review (Section 3) showed that rigid degree structures exclude mid-career professionals. The RADAR-aim course structure should prioritise inclusivity through a hybrid design:

Asynchronous components should deliver foundational content through online materials, enabling adaptive learning paths tailored to individual progress and prior knowledge. In courses serving learners with heterogeneous backgrounds, the asynchronous section should allow participants to concentrate on subjects that are new to them while progressing quickly through familiar material. This is particularly important for AI-sustainability courses, where a data scientist may need to build sustainability literacy while a policy professional needs AI fundamentals.

Synchronous components (either on-campus or online) should be reserved for highly interactive sessions: collaborative problem-solving, group projects, expert discussions, and the application of concepts to real-world cases. All participants, regardless of background, should arrive at synchronous sessions prepared to actively engage.

Mentoring and support should be designed recognising that micro-credential participants have shorter time commitments and may have limited physical campus presence. AI-driven tutoring tools can complement human mentors in providing flexible, extended support.

6.4. Create a Supportive Learning Environment

Classes should employ a variety of pedagogical approaches: lectures, workshops, seminars, class discussions, workgroups, flipped classrooms, project-based learning, and game-based learning. When delivered digitally, these characteristics should be reflected in the features of the supporting platform and digital content formats (such as interactive H5P videos).

Interaction between instructors and participants, and among participants themselves, is essential given the interdisciplinary nature of the targeted learning outcomes. Cross-disciplinary collaboration is a core mechanism, not an add-on, for developing the competencies that the program aims to build.

6.5. Define a Modular Credit Architecture

The RADAR-aim program should adopt a granular credit architecture that maximises flexibility and stackability. Drawing on the consortium's design decisions, the recommended structure uses 1 ECTS as the basic building block, with modules designed at standard sizes of 3, 6, 9, or 15 ECTS. This granularity allows individual micro-credentials to be embedded in existing study programs at partner institutions, whether bachelor, master, postgraduate, or lifelong learning courses, while also enabling learners to accumulate credits toward the full 15–30 ECTS program.

The modular design serves several purposes. For students enrolled in degree programs, individual modules can substitute for elective courses or complement existing specialisations. For working professionals, the small credit units reduce the commitment barrier and allow learning to be distributed across longer periods. For institutions, the stand-alone character of each module means they can be offered independently or combined without requiring structural changes to existing curricula.

6.6. Build Transparency and Quality to Foster Recognition

In line with the European Council Recommendation and the ETF guidelines assessed in the the content and framework analysis (Section 5), micro-credentials on AI and sustainability should be:

- **Classified** in terms of their EQF level (level 6 for bachelor, level 7 for master, and level 8 for third cycle where applicable).
- **Described in detail** regarding intended learning outcomes, assessment mechanisms, and expected workload in ECTS, ensuring transparency and comparability.
- **Evaluated** according to existing quality assurance systems, with adaptations to make QA processes proportionate to the scope of short learning courses.
- **Monitored and reviewed regularly** to verify alignment between learning outcomes, assessments, and course content in a rapidly evolving field where AI techniques and sustainability challenges both shift continuously.

6.7. Curriculum Architecture: Maturity-Based Tiers

Synthesising the pathway approach with the gap analysis findings, the RADAR-aim curriculum should follow a tiered architecture. This tiered structure maps directly onto the layered pattern of gaps identified in the Section 5.2.6: foundational gaps in mutual literacy, advanced gaps in critical interpretation and responsible use, and domain-specific gaps in techniques most relevant to sustainability applications.

Tier 1: Basic Knowledge targets bachelor students, early-career professionals, and learners with no prior exposure to either AI or sustainability. The goal is to establish digital competence and sustainability literacy. For technical profiles (Pathways 1 and 2), foundational modules focus on sustainability context, systems thinking, and the SDG framework. For non-technical profiles (Pathways 3 and 4), foundational modules focus on AI literacy, i.e. understanding what AI systems can and cannot do, how they process data, and how to critically evaluate their outputs. Diagnostic assessment at entry directs each learner to the appropriate foundational content, ensuring that no time is spent on material already mastered.

Tier 2: Advanced Knowledge targets master's students, PhD candidates, and experienced lifelong learners. Modules at this level focus on the transversal competences that emerged as critical gaps: interpreting AI results in domain-specific contexts, auditing systems for bias, managing responsible AI implementation, and, notably, the responsible use of generative AI, including understanding the ethical implications, energy consumption, and application potential of large language models. The modular system allows learners with existing expertise to validate prior knowledge and bypass foundational content. At this tier, the differences between learner profiles begin to narrow, as all pathways converge on the shared challenge of applying AI responsibly and effectively.

Tier 3: Domain-Specific Application allows specialisation in vertical sustainability challenges (e.g., AI for circular economy, AI for urban planning, AI for climate adaptation). This tier directly addresses the content gaps identified in the the content and framework analysis (Section 5) by providing focused modules on advanced techniques (multi-objective optimisation, uncertainty handling, model transparency, advanced pattern recognition) within specific sustainability domains. At this level, modules are designed to serve learners across all four pathways, with the

technical depth of engagement adapted through pathway-specific assessment tasks rather than separate content streams.

6.8. Addressing Content Gaps

Based on the gap analysis in the the content and framework analysis (Section 5), the RADAR-aim curriculum should prioritise five content areas that are systematically underrepresented in existing offerings:

Responsible use of generative AI. Beyond traditional predictive models, learners must understand the specific ethical implications, energy consumption issues, and application potential of large language models and other generative systems.

Optimisation for competing objectives. Standard data science education focuses on prediction accuracy; sustainability challenges require balancing trade-offs (economic cost versus carbon footprint, development versus conservation). Multi-objective optimisation methods should be a core component.

Uncertainty and non-stationarity. Climate change means historical data is no longer a reliable predictor. Learners must build robust AI systems that function under distributional shift and communicate uncertainty effectively to decision-makers.

Model transparency and accountability. As AI systems increasingly inform high-stakes environmental decisions, learners must understand interpretability methods, sensitivity analysis, and techniques for generating human-understandable explanations of model behaviour, competencies needed for stakeholder trust and regulatory compliance.

Advanced pattern recognition for complex environmental data. Sustainability problems involve interconnected, multi-modal, and temporal data. Learners need exposure to network analysis, time series methods, and techniques for integrating heterogeneous data sources (satellite imagery with ground sensors, textual reports with numerical measurements).

6.9. Competence Framework for Learning Outcome Development

The learning outcomes for each module should be grounded in a coherent competence framework that spans all four learner pathways and all three maturity tiers. Building on the consortium's stakeholder consultation design (Section 4), the framework is organised around five transversal competence domains:

1. **AI Literacy and Critical Understanding.** The ability to understand AI capabilities and limitations, evaluate outputs critically, and engage with AI systems at a level appropriate to one's professional role.
2. **Sustainability Orientation and Systems Thinking.** The ability to recognise sustainability as an interconnected system, identify trade-offs and feedback loops, and frame problems within environmental, social, and economic contexts.
3. **Ethics, Responsibility and Governance.** The ability to identify ethical dimensions of AI deployment, understand relevant regulatory frameworks, and take responsibility for the societal and environmental consequences of AI-informed decisions.
4. **Decision-Making, Action and AI Integration.** The ability to use AI outputs for evidence-based decision-making, integrate computational results into professional workflows, and translate analytical findings into actionable strategies.

5. **Collaboration, Learning and Reflexivity.** The ability to work effectively across disciplinary boundaries, engage in continuous professional development, and reflect critically on one's own assumptions and learning process.

Each domain applies across all four pathways but is operationalised differently depending on the learner's background and the tier level. At Tier 1, competences are expressed as foundational literacy; at Tier 2, as critical application and responsible use; at Tier 3, as domain-specific expertise. This structure ensures that every module's learning outcomes can be mapped to both a competence domain and a maturity level, providing the transparency and comparability required by the European micro-credential standards assessed in the the content and framework analysis (Section 5).

7. Positioning Within Existing Micro-Credential Offerings

To position the RADAR-aim offering against what currently exists, a supplementary review identified 32 micro-credential and short-course programs related to AI, sustainability, or their intersection across 15 countries. The review serves not as a comprehensive analysis (which would fall within the scope of the landscape review (Section 3)) but as a positioning exercise to verify that the recommendations above address a genuine gap.

The existing micro-credential offering is overwhelmingly oriented toward general AI literacy. The most prevalent themes are AI ethics and governance (41%), business applications of AI (34%), machine learning fundamentals (34%), and generative AI techniques (31%). Advanced AI techniques are largely absent: deep learning, NLP, and reinforcement learning each appear in fewer than 7% of programs. Most critically, only 1 of the 32 programs (3%) contains any reference to sustainability, the environment, or climate. No program structures its curriculum around the application of AI to sustainability challenges.

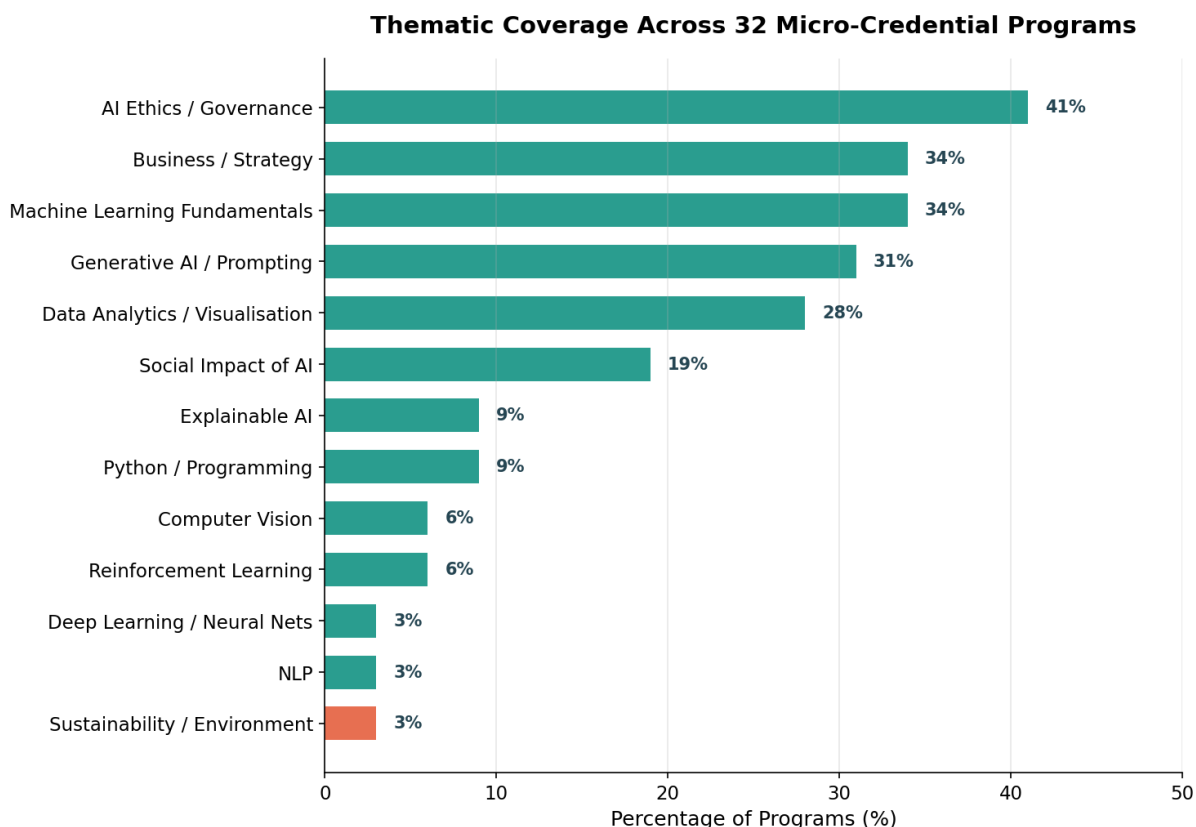


Figure 15: Thematic coverage across 32 micro-credential programs

This gap is even more pronounced than in the full-degree landscape. Where 14.5% of sustainability-focused postgraduate programs include at least some AI content (see landscape review (Section 3)), the micro-credential equivalent is 3.1%, a near-fivefold difference. The shorter format and demand-driven design of micro-credentials has, so far, reinforced rather than bridged disciplinary silos between AI education and sustainability education.

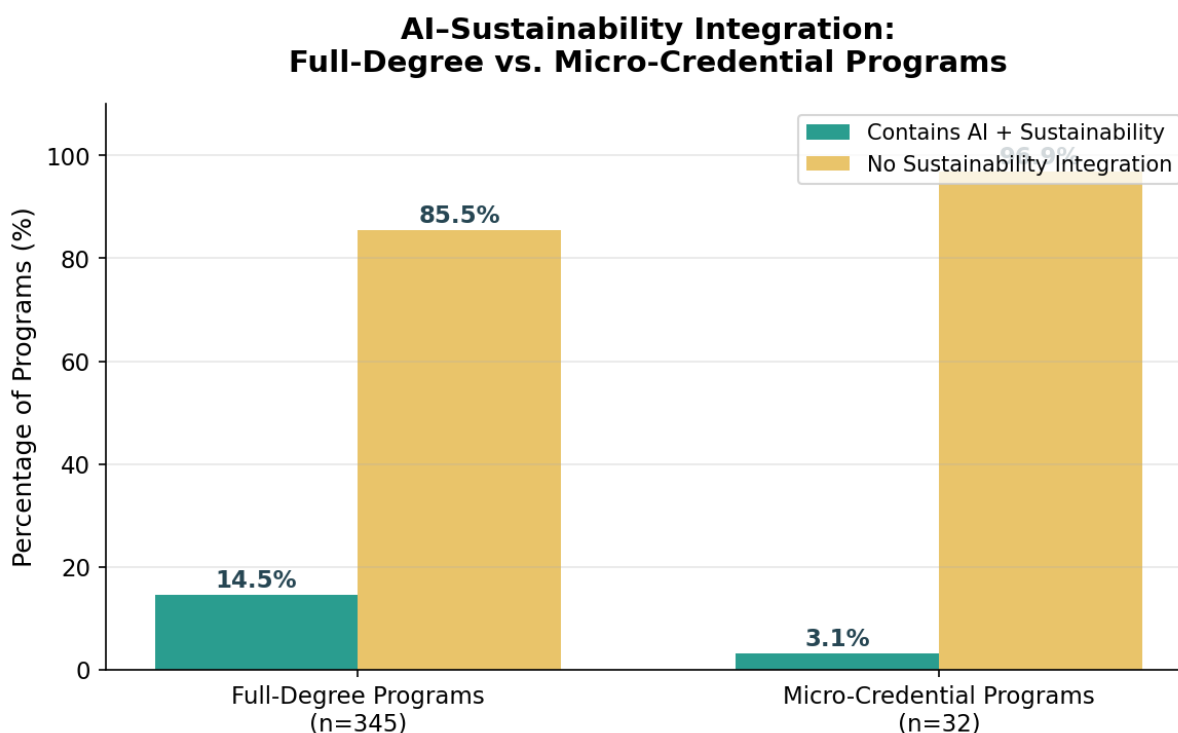


Figure 16: AI-sustainability integration: full-degree vs. micro-credential programs

Note: The two bars reflect different base populations. The full-degree figure (n=345) represents sustainability-focused programs assessed for AI content; the non-shaded portion indicates sustainability programs without AI integration, not programs lacking sustainability. The micro-credential figure (n=32) represents AI and general programs assessed for sustainability content. Both bars measure the proportion of programs that combine AI and sustainability (the metric of interest) but from opposite disciplinary starting points.

Structurally, existing micro-credentials vary widely, from short courses of a few days to programs of several months, with credit denominations ranging from 5 to 30 ECTS. Most target working professionals and offer flexible or fully online delivery. Few offer formal ECTS credit or quality-assured assessment. This diversity reinforces the importance of the RADAR-aim commitment to ECTS-denominated, quality-assured credentials that are stackable and formally recognised within the European higher education area.

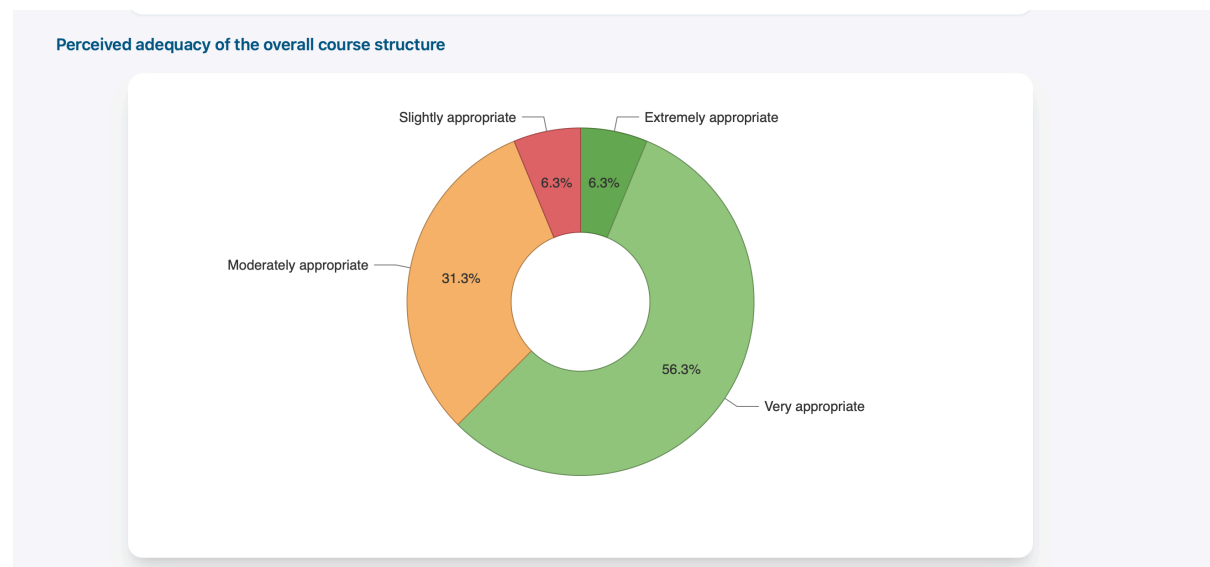
8. Stakeholder Consultation Results

The stakeholder consultation was designed to validate and refine the design recommendations derived from the landscape, standards, and content analyses.

8.1. AI and Data Science Profile

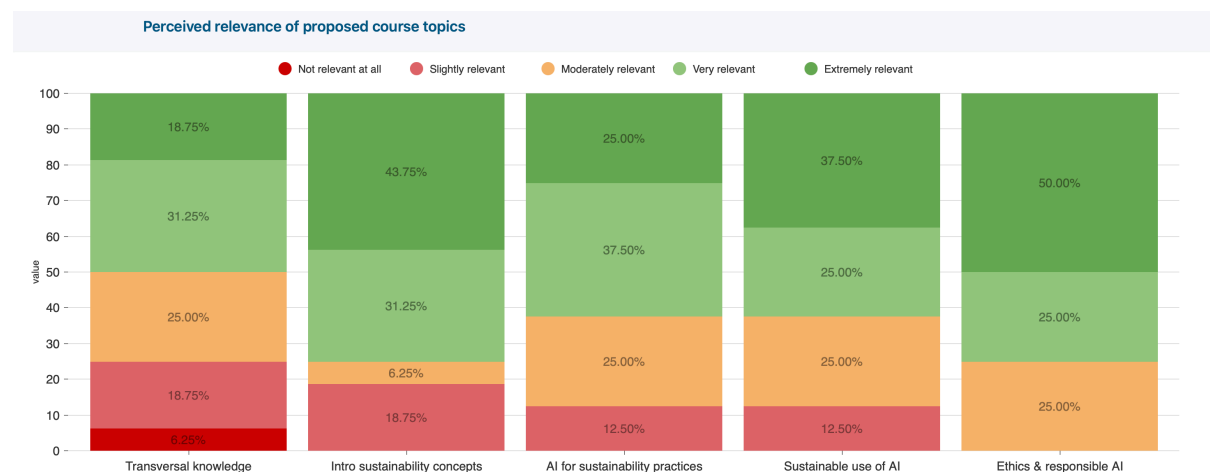
Sample composition. The AI and Data Science profile comprises 21 respondents, predominantly from higher education contexts. Educators and professors represent the largest group (28.6%), followed by PhD candidates (19.0%), with master-level participants and lifelong learners each at 14.3%. A large majority (80.0%) identify Artificial Intelligence as their primary field, with 20.0% reporting Data Science. Participants are mainly based in Belgium (62.5%), Portugal (25.0%), and Italy (12.5%). More than half (56.3%) have over six years of experience, indicating a relatively mature group.

Course structure and topics. The proposed three-tier programme structure receives positive evaluation. A majority (56.3%) rate it as *very appropriate* and 6.3% as *extremely appropriate*, with a further 31.3% indicating *moderately appropriate*. Only 6.3% perceive it as *slightly appropriate*.



Perceived adequacy of the overall course structure – AI and Data Science profile

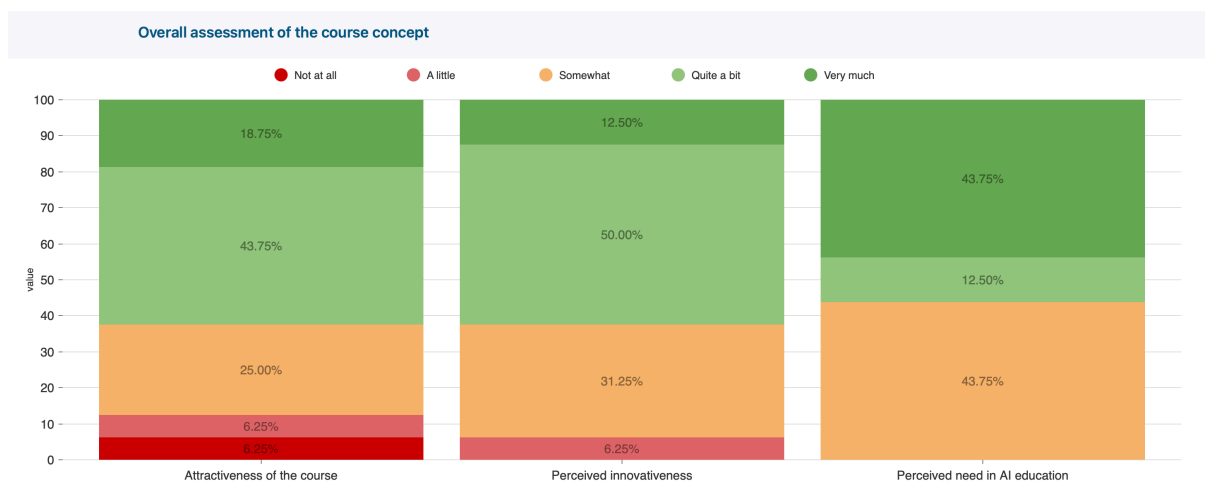
All proposed topics are considered relevant. Ethics and responsible AI receives the strongest endorsement, with 50% rating it *extremely relevant* and 25% *very relevant*. Introduction to sustainability concepts is also highly valued (43.75% *extremely relevant*, 31.25% *very relevant*). Sustainable use of AI and AI for sustainability practices each receive majority support in the upper relevance categories. Transversal knowledge (systems thinking, critical thinking, futures thinking) is rated positively, though with a higher share of *moderately relevant* responses. Open-ended comments emphasise the importance of addressing the negative consequences of unsustainable or unethical AI through concrete examples, reinforcing the quantitative emphasis on ethics and sustainability impact.



Perceived relevance of proposed course topics – AI and Data Science profile

Course concept assessment. The course concept is broadly supported. Perceived need in AI education receives the strongest result: 43.75% rate it *very much* and 12.50% *quite a bit*, with the

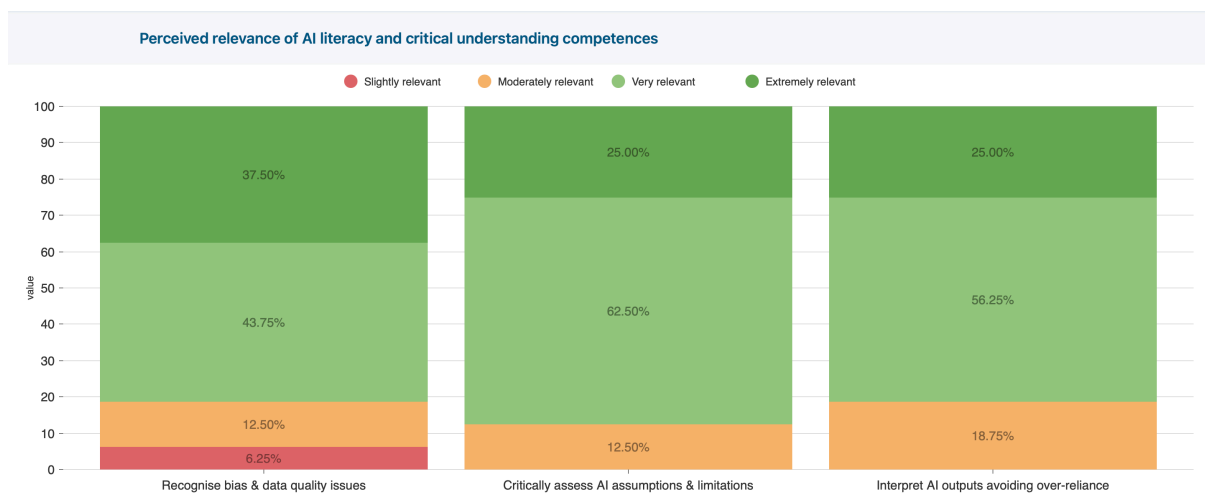
remaining 43.75% selecting *somewhat*. Innovativeness is rated positively (50% *quite a bit*, 12.50% *very much*). Attractiveness shows 43.75% *quite a bit* and 18.75% *very much*.



Overall assessment of the course concept – AI and Data Science profile

Competence domain evaluations. All five competence domains receive high relevance ratings, with responses concentrated between *very relevant* and *extremely relevant*.

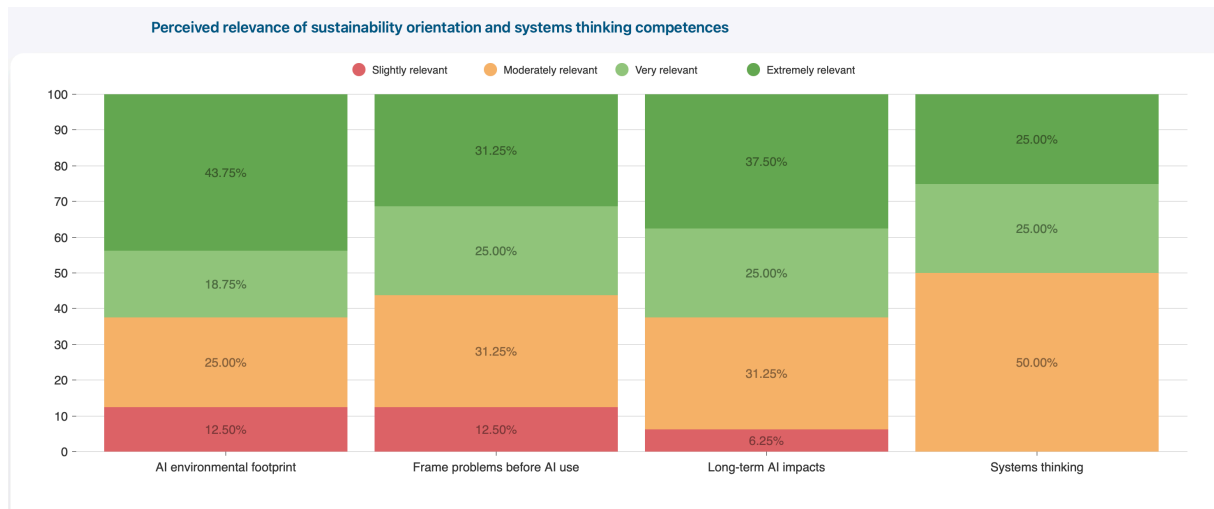
In *AI Literacy and Critical Understanding*, the ability to critically assess AI assumptions and limitations is the most valued competence (62.5% *very relevant*, 25% *extremely relevant*). Interpreting AI outputs while avoiding over-reliance shows a similar distribution. Recognising bias and data quality issues also achieves high relevance (43.75% *very relevant*, 37.5% *extremely relevant*). The pattern confirms a mature orientation toward reflective, not merely technical, use of AI systems.



Perceived relevance of AI literacy and critical understanding competences – AI and Data Science profile

In *Sustainability Orientation and Systems Thinking*, awareness of the AI environmental footprint receives the highest share of *extremely relevant* responses (43.75%), followed by long-term AI impacts (37.5%). Systems thinking, although considered important, presents a higher share of

moderately relevant responses (50%), suggesting it is perceived as more abstract or less immediately operational.



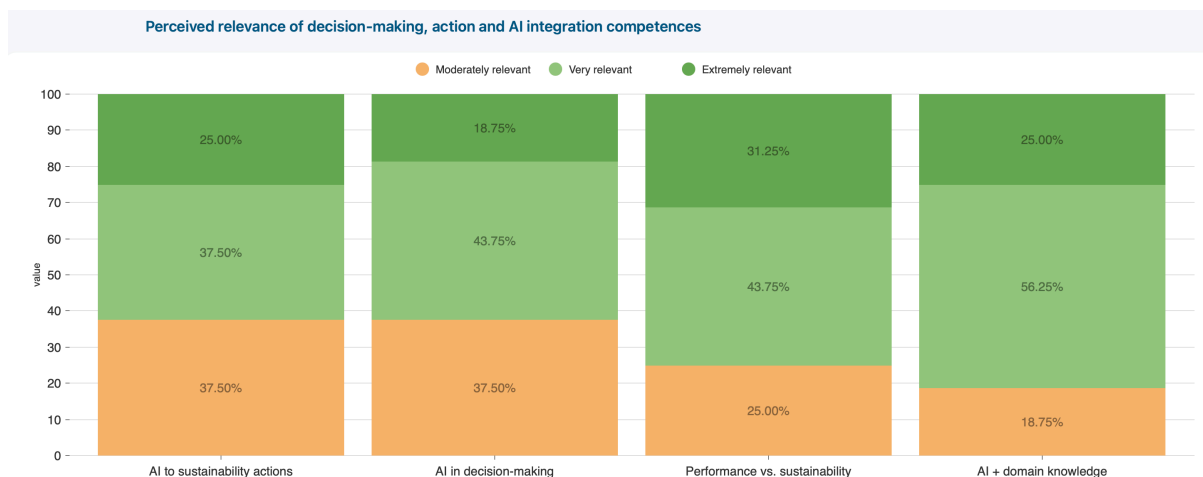
Perceived relevance of sustainability orientation and systems thinking competences – AI and Data Science profile

Ethics, Responsibility and Governance is one of the strongest domains in terms of consensus. Ethical issues in AI reaches 81.25% *very relevant*. Responsible AI choices and fairness, inclusion and bias also show strong concentration in the highest relevance categories. These competences are perceived as structural elements of the desired professional profile, not as supplementary considerations.



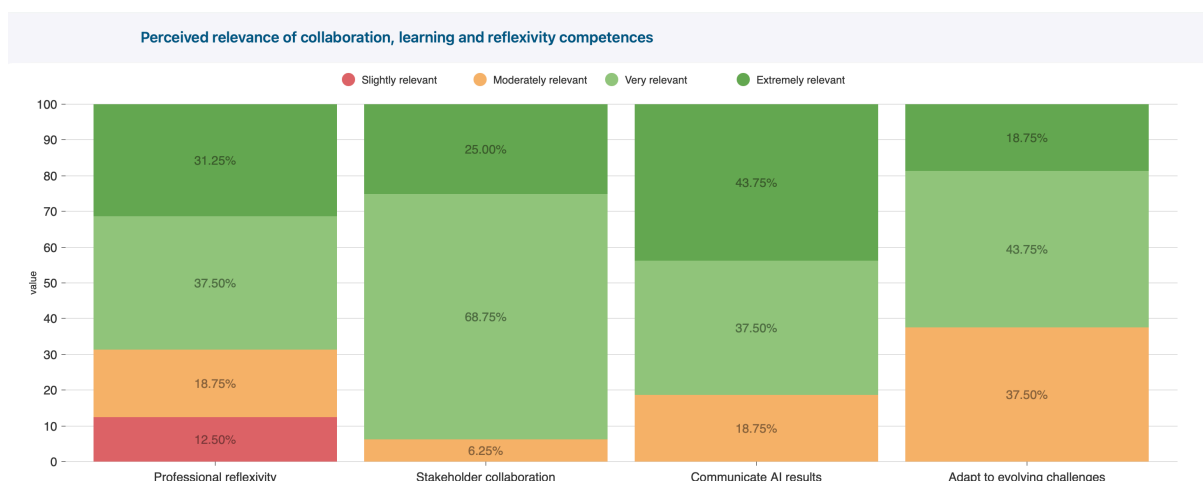
Perceived relevance of ethics, responsibility and governance competences – AI and Data Science profile

In *Decision-Making, Action and AI Integration*, combining AI with domain knowledge receives particularly high evaluation (56.25% *very relevant*, 25% *extremely relevant*). Managing performance-versus-sustainability trade-offs is also strongly endorsed (43.75% *very relevant*, 31.25% *extremely relevant*). The pattern signals interest in decision-making and managerial capabilities alongside analytical skills.



Perceived relevance of decision-making, action and AI integration competences – AI and Data Science profile

In *Collaboration, Learning and Reflexivity*, stakeholder collaboration is the most valued competence (68.75% *very relevant*, 25% *extremely relevant*), followed by communicating AI results (43.75% *extremely relevant*). Professional reflexivity and adaptability are considered important but slightly less prioritised compared to ethical or decision-making dimensions.



Perceived relevance of collaboration, learning and reflexivity competences – AI and Data Science profile

An open-ended comment reinforces the orientation emerging from the quantitative results: sustainability assessment should be systematically integrated into all AI applications, regardless of scale, rather than reserved for high-impact systems only. This reflects an expectation that sustainability should function as a default design principle.

8.2. Engineering and Design Profile

Sample composition. The Engineering and Design profile comprises 9 respondents, distributed across academic, instructional, and research-related positions. A majority (62.5%) identify primarily with Engineering, while 37.5% report Sustainability or Environmental expertise. Most respondents are from Portugal (80%), with a smaller share from Belgium (20%). The majority report medium to long-term experience: 40% indicate 6-10 years and 40% more than 10 years.

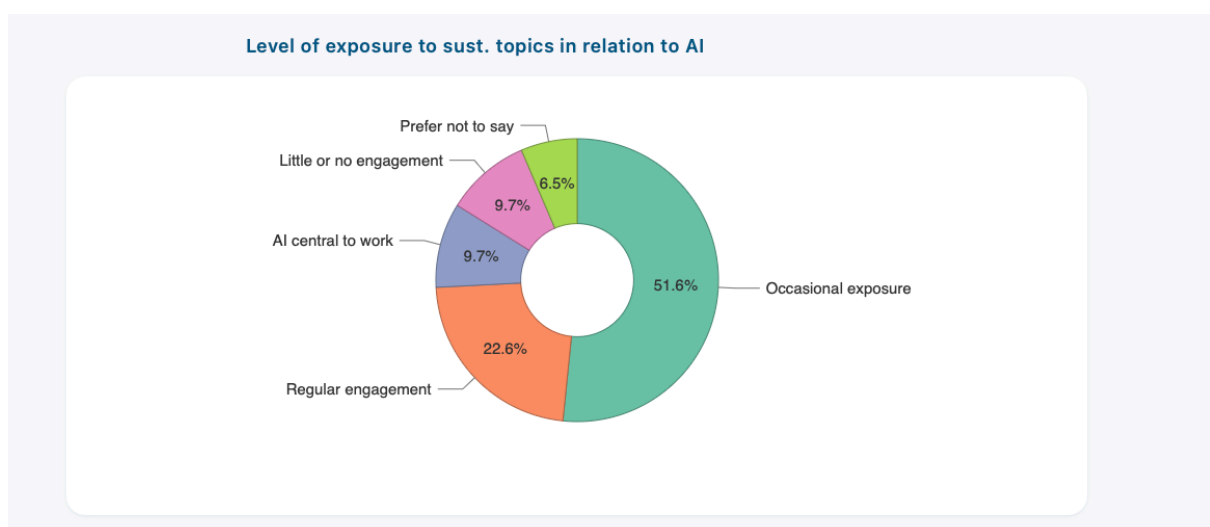
Exposure to sustainability topics in relation to AI is heterogeneous, with 40% reporting occasional exposure, 40% indicating little or no engagement, and 20% reporting regular engagement.

Given the small sample size (n=9), this section reports demographic composition and qualitative findings. Detailed quantitative breakdowns for course structure, topic relevance, course concept, and competence domain ratings are not reported at the individual-profile level, as percentage-based distributions would not be meaningful for a group of this size. These results will be consolidated with additional responses collected during WP3 and reported in full in this report.

Qualitative findings. Despite the limited number of respondents, qualitative feedback provides useful directional signals consistent with the patterns observed in the larger profiles. Respondents stress the importance of including basic sustainability knowledge at the beginning of the course, ensuring that all participants share a common foundation before engaging with more advanced AI components. One respondent specifically highlights the relevance of AI applications in building construction and environmental certification, reflecting interest in concrete sectoral use cases. The emphasis on applied, governance-aware AI competences is evident, with particular weight placed on the ability to contextualise and validate AI-generated outputs within professional engineering practice. These orientations align with the cross-profile emphasis on ethics, governance, and practice-oriented learning identified in Section 4.5.5, while reflecting a distinctly implementation-focused perspective shaped by engineering and design workflows.

8.3. Social Sciences and Management Profile

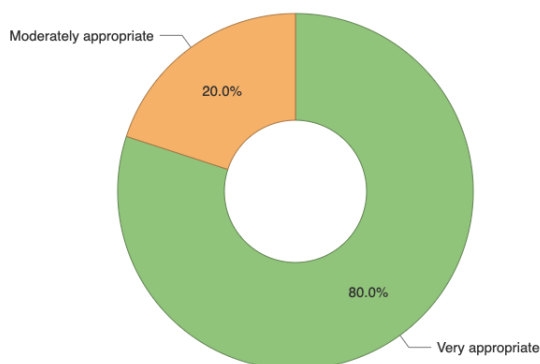
Sample composition. The Social Sciences and Management profile is the largest, with 47 respondents. The distribution of roles shows a balanced mix: bachelor and master students each represent 21.4%, PhD candidates 19%, and educators/professors also 19%. Business and Management is the dominant field of study (44.0%), followed by Economics (22.0%) and Sustainability/Environmental studies (16.0%). The majority of participants are from Italy (74.2%), followed by Germany (16.1%) and Belgium (9.7%). Most respondents are early- to mid-career, with 51.6% reporting 2-5 years of experience. Regarding exposure to AI in relation to sustainability, the majority (51.6%) report occasional engagement, while 22.6% indicate regular exposure.



Exposure to sustainability topics in relation to AI – Social Sciences and Management profile

Course structure and topics. The proposed structure receives very high approval: 77.4% rate it as *very appropriate* and 12.9% as *extremely appropriate*, with only 6.5% selecting *moderately appropriate* and 3.2% *slightly appropriate*.

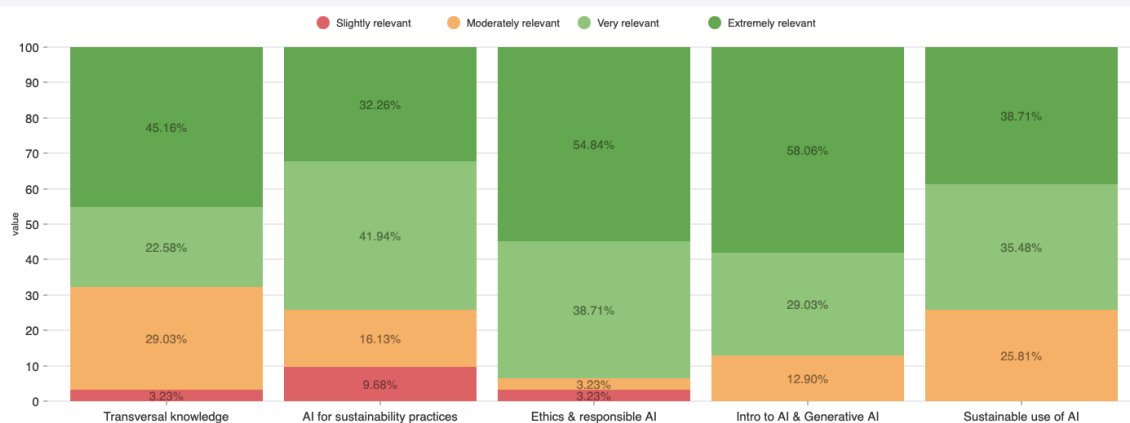
Perceived adequacy of the overall course structure



Perceived adequacy of the overall course structure – Social Sciences and Management profile

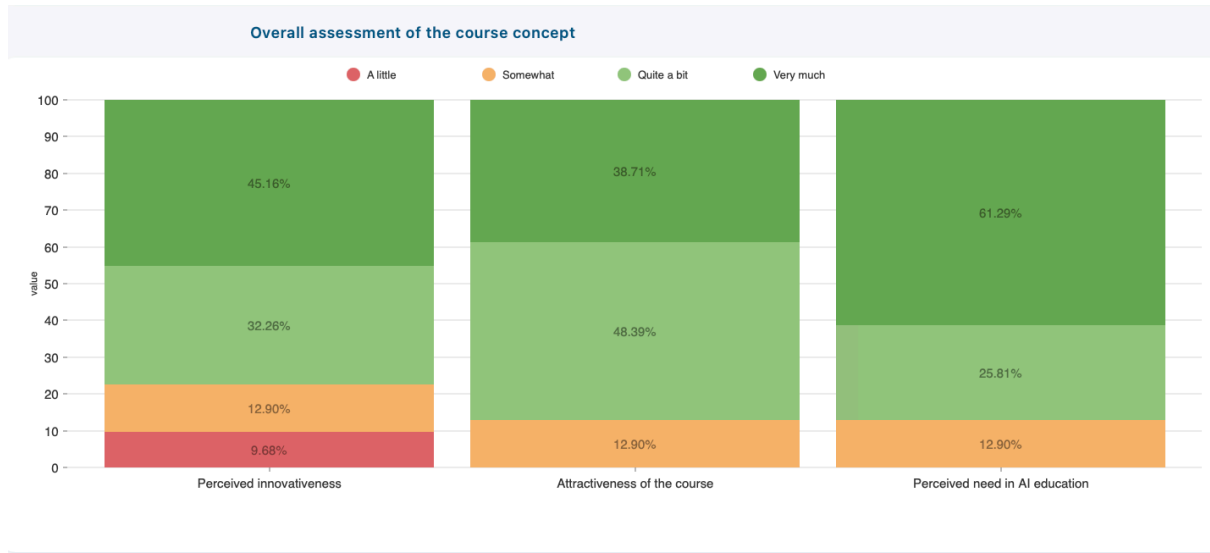
Topic relevance is consistently high. Ethics and responsible AI and introduction to AI and generative AI receive the strongest concentration of *extremely relevant* ratings (54.84% and 58.06% respectively). AI for sustainability practices and sustainable use of AI also show strong positive evaluation, with clear majorities in the upper relevance categories. Transversal knowledge is likewise positively evaluated. Open-ended responses suggest broadening the scope to include AI in everyday life, international AI governance, and emerging risks such as misinformation and geopolitical implications.

Perceived relevance of proposed course topics



Perceived relevance of proposed course topics – Social Sciences and Management profile

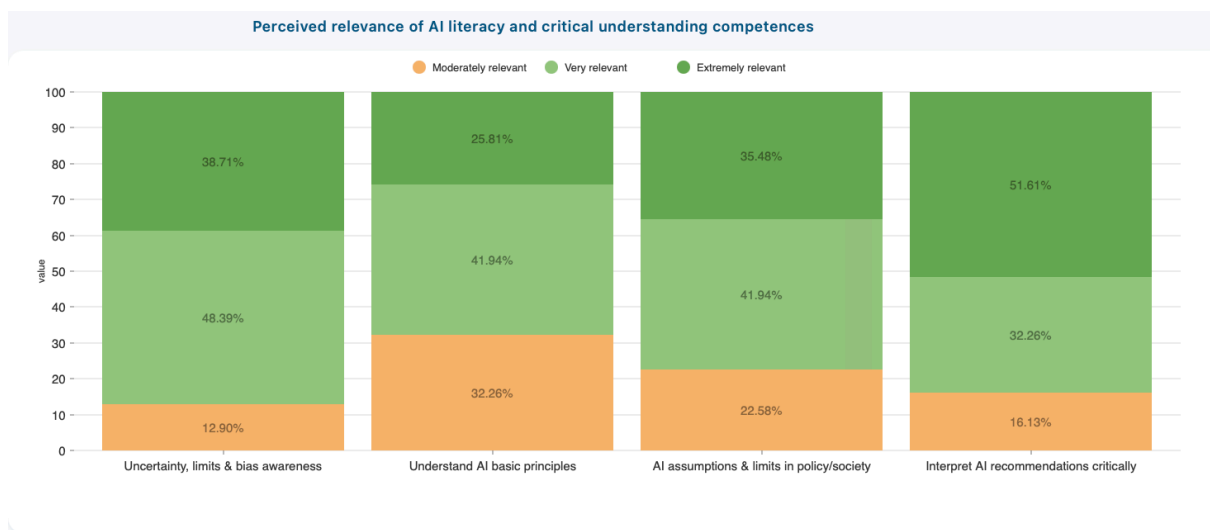
Course concept assessment. The course concept receives the strongest endorsement of any profile on perceived need: 61.29% indicate *very much* and 25.81% *quite a bit*. Innovativeness is rated positively (45.16% *very much*, 32.26% *quite a bit*), and attractiveness also shows strong support (38.71% *very much*, 48.39% *quite a bit*).



Overall assessment of the course concept – Social Sciences and Management profile

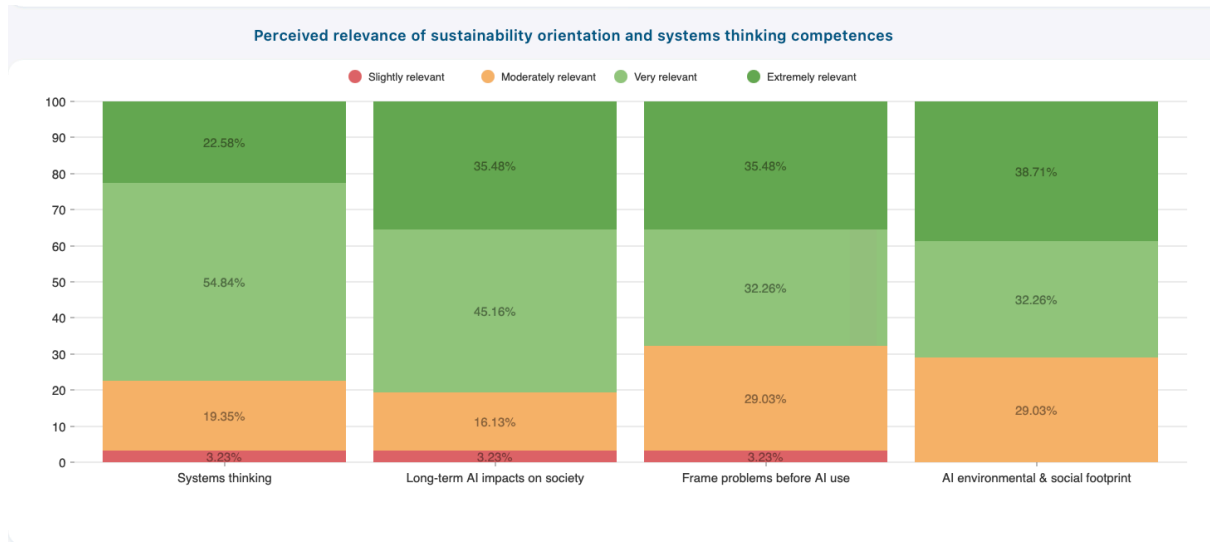
Competence domain evaluations. All five domains receive high endorsement.

In *AI Literacy and Critical Understanding*, the ability to interpret AI recommendations critically stands out (51.61% *extremely relevant*). Awareness of uncertainty, limits, and bias reaches 38.71% *extremely relevant*. Understanding basic AI principles, while positively evaluated, shows a higher share of *moderately relevant* responses (32.26%), suggesting that respondents prioritise critical evaluation over technical depth.



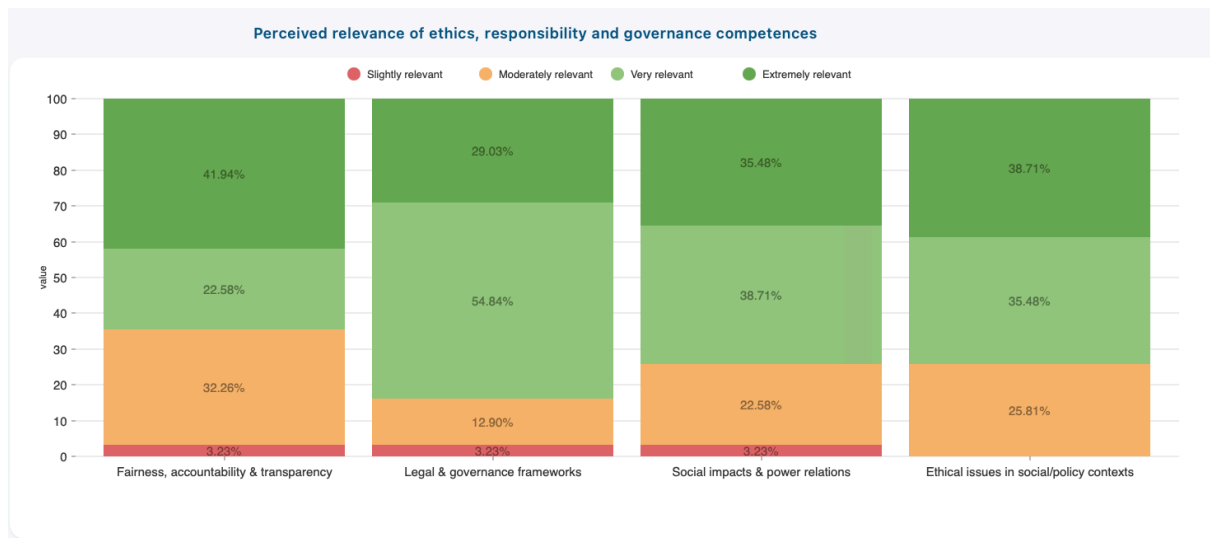
Perceived relevance of AI literacy and critical understanding competences – Social Sciences and Management profile

Sustainability Orientation and Systems Thinking receives strong support. Systems thinking records 54.84% *very relevant* and 22.58% *extremely relevant*. Long-term AI impacts on society reaches 35.48% *extremely relevant*. Competences related to framing problems before AI use and assessing AI's environmental and social footprint are similarly concentrated in the upper relevance levels.



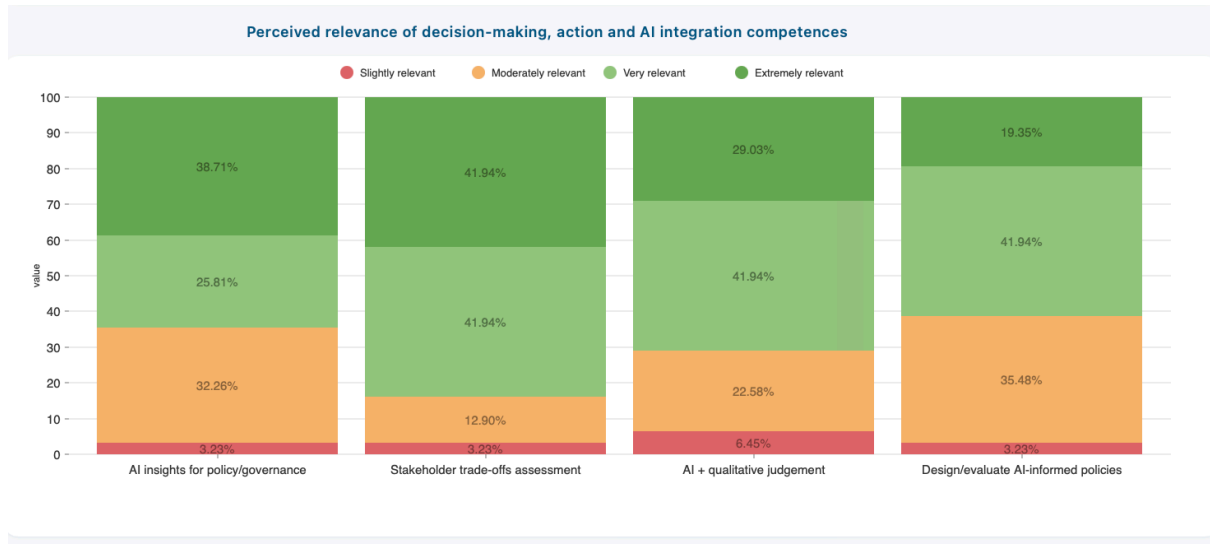
Perceived relevance of sustainability orientation and systems thinking competences – Social Sciences and Management profile

Ethics, Responsibility and Governance shows particularly strong endorsement. Fairness, accountability, and transparency are rated *extremely relevant* by 41.94% and ethical issues in social and policy contexts by 38.71%. Legal and governance frameworks are predominantly evaluated as *very relevant* (54.84%), indicating broad support for institutional and regulatory competences.



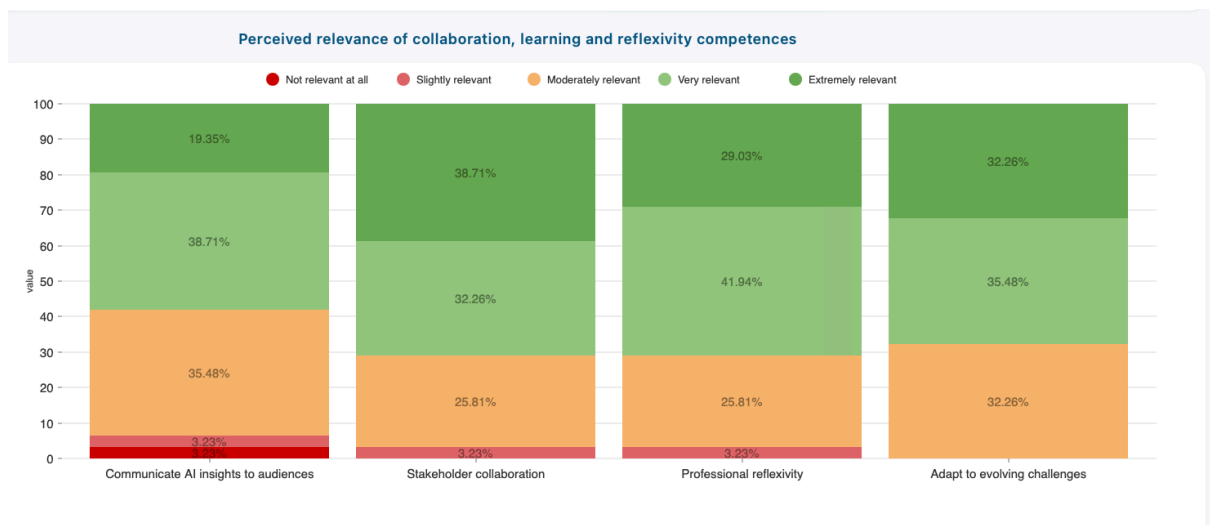
Perceived relevance of ethics, responsibility and governance competences – Social Sciences and Management profile

In *Decision-Making, Action and AI Integration*, stakeholder trade-off assessment shows 41.94% *very relevant* and 41.94% *extremely relevant*. Combining AI insights with qualitative judgement records 41.94% *very relevant* and 29.03% *extremely relevant*. The pattern indicates that Social Sciences respondents value the integration of AI-based evidence with contextual knowledge and qualitative reasoning.



Perceived relevance of decision-making, action and AI integration competences – Social Sciences and Management profile

Collaboration, Learning and Reflexivity is recognised as relevant, with stakeholder collaboration reaching 38.71% *extremely relevant* and professional reflexivity 29.03%. Communication of AI insights shows a more moderate spread, with 35.48% *moderately relevant* and 38.71% *very relevant*.

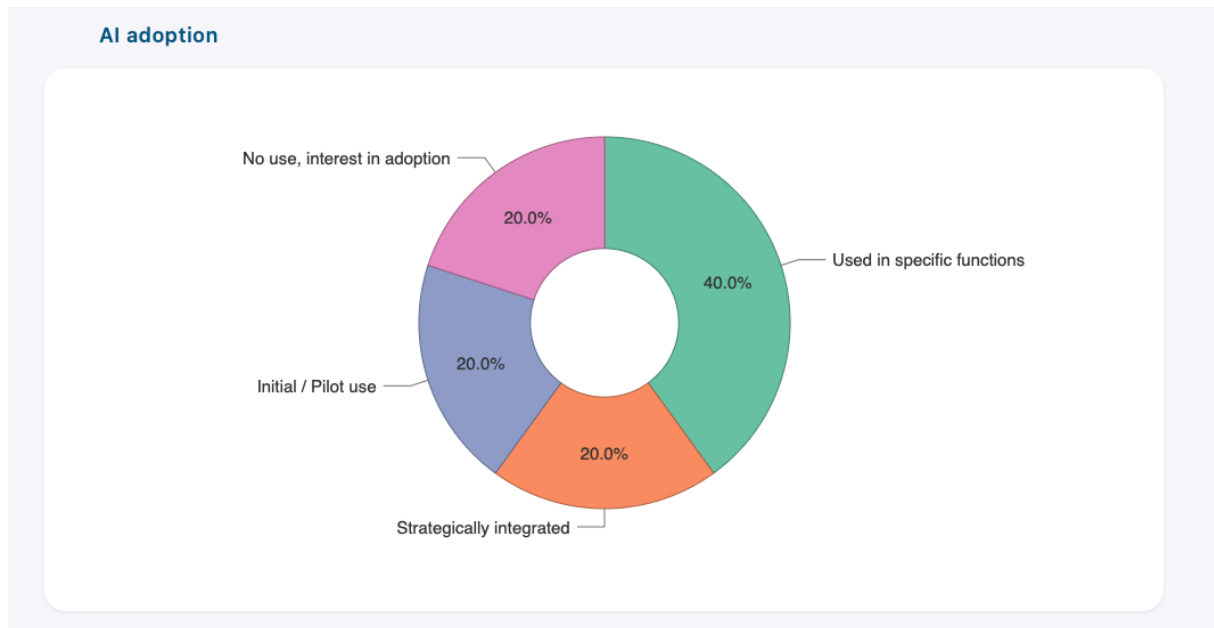


Perceived relevance of collaboration, learning and reflexivity competences – Social Sciences and Management profile

Open-ended responses reinforce the quantitative pattern, highlighting two recurrent priorities: deeper treatment of risk and environmental impact (including the ability to conduct risk assessments, data quality management, and addressing over-reliance on AI), and a more explicit integration of practical, application-oriented learning formats (case studies, real-case simulations, modules where concepts can be tested in practice). Several respondents describe the course concept as “strong and timely” while emphasising that its applied dimension could be further strengthened.

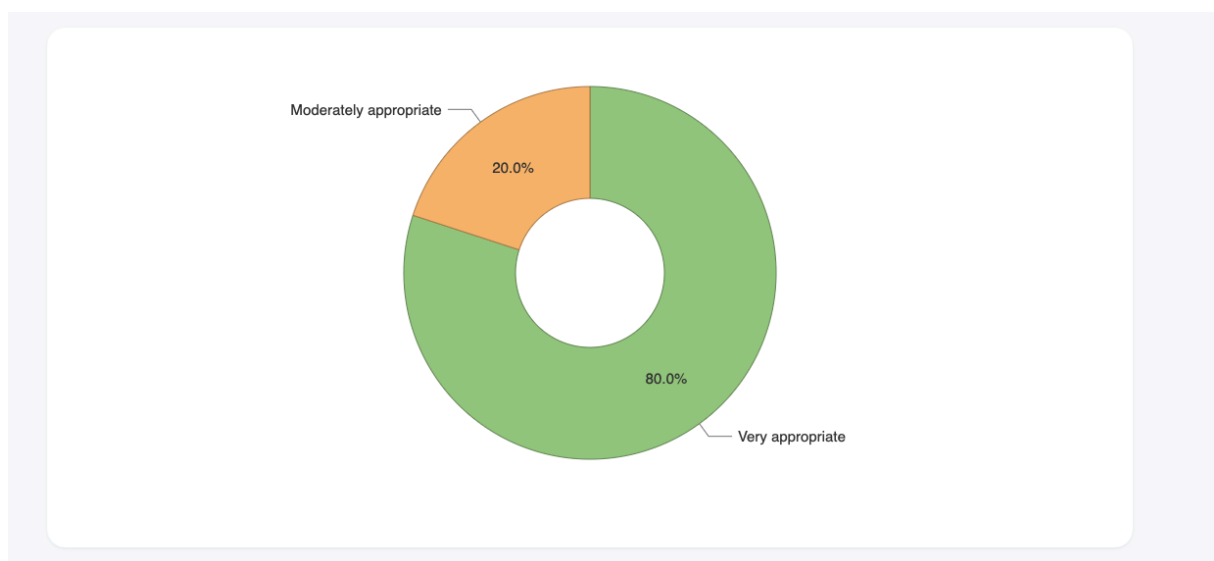
8.4. Companies and Organisations Profile

Sample composition. The Companies profile comprises 9 respondents distributed across roles reflecting both technical and strategic orientations: 40% in digital, data, or AI-related roles; 20% in innovation/strategy; 20% in sustainability/ESG-related roles; and 20% as external experts or consultants. In terms of sector, 40% come from sustainability/ESG consulting, followed by energy (20%), environmental services (20%), and digital/IT services (20%). The profile is evenly split between Italy and Portugal. Organisations are predominantly large (40%) or medium-sized (40%). Regarding AI adoption, 40% report AI used in specific functions, 20% describe strategic integration, 20% indicate pilot use, and 20% report no current use but interest in adoption.



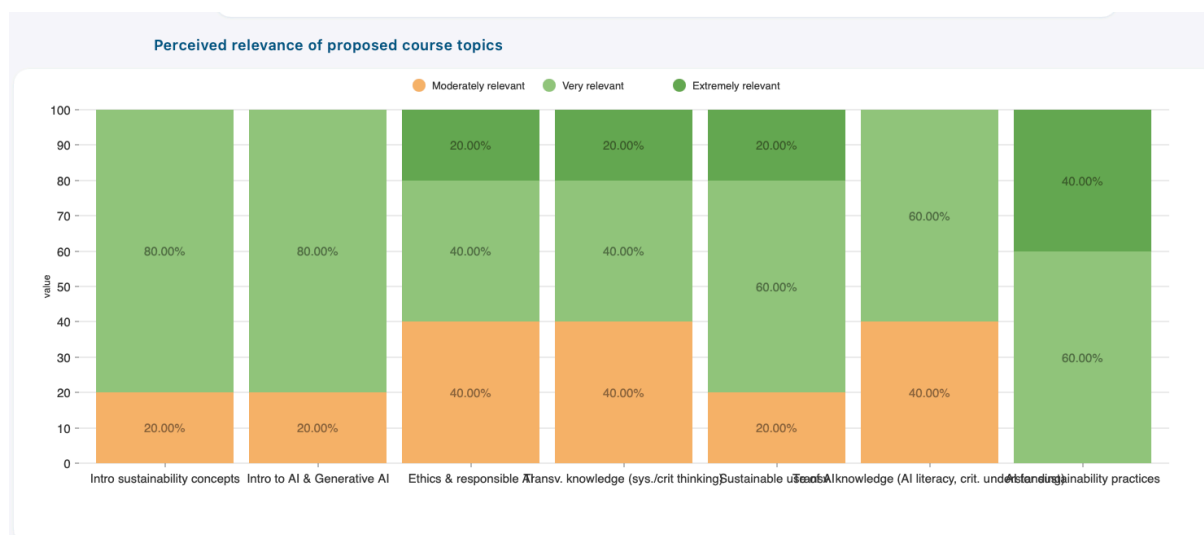
AI adoption stage – Companies and Organisations profile

Course structure and topics. The proposed structure receives very high endorsement: 80% rate it as *very appropriate* and 20% as *moderately appropriate*, with no negative evaluations.



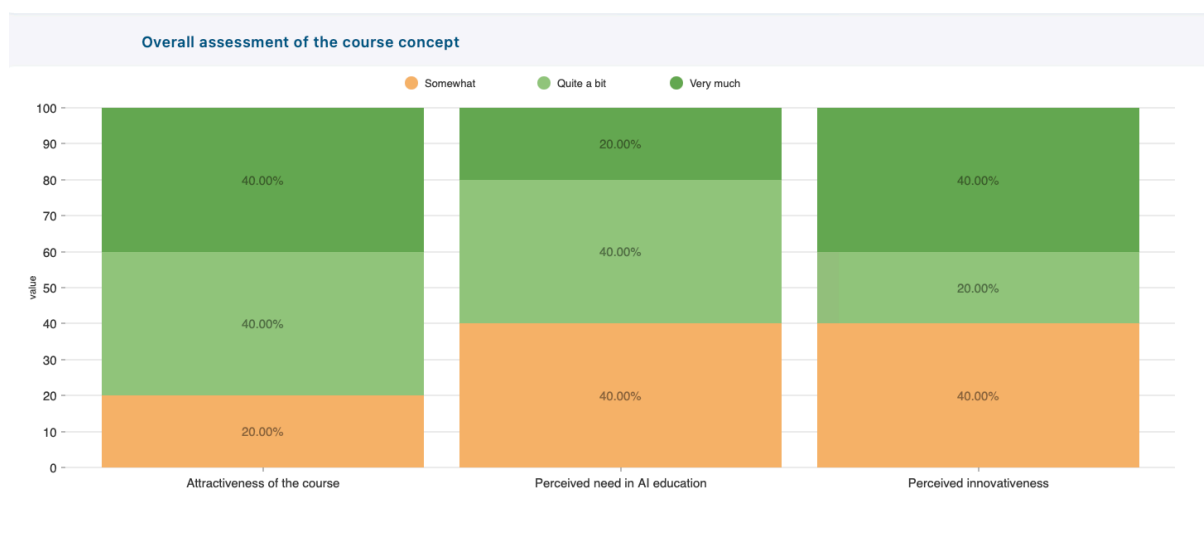
Perceived adequacy of the overall course structure – Companies and Organisations profile

Topic relevance is consistently high, with a distinctive pattern compared to the academic profiles. Introductory modules on sustainability concepts and on AI and generative AI receive particularly strong endorsement (80% *extremely relevant* each). Sustainable use of AI (60% *extremely relevant*) and AI for sustainability practices (40% *extremely relevant*) are also strongly supported. Ethics and responsible AI and transversal knowledge, while positively evaluated, show a slightly more balanced distribution (40% *moderately relevant*, 40% *very relevant*, 20% *extremely relevant*), suggesting that organisations prioritise practical and operational dimensions while maintaining interest in responsible-use aspects.



Perceived relevance of proposed course topics – Companies and Organisations profile

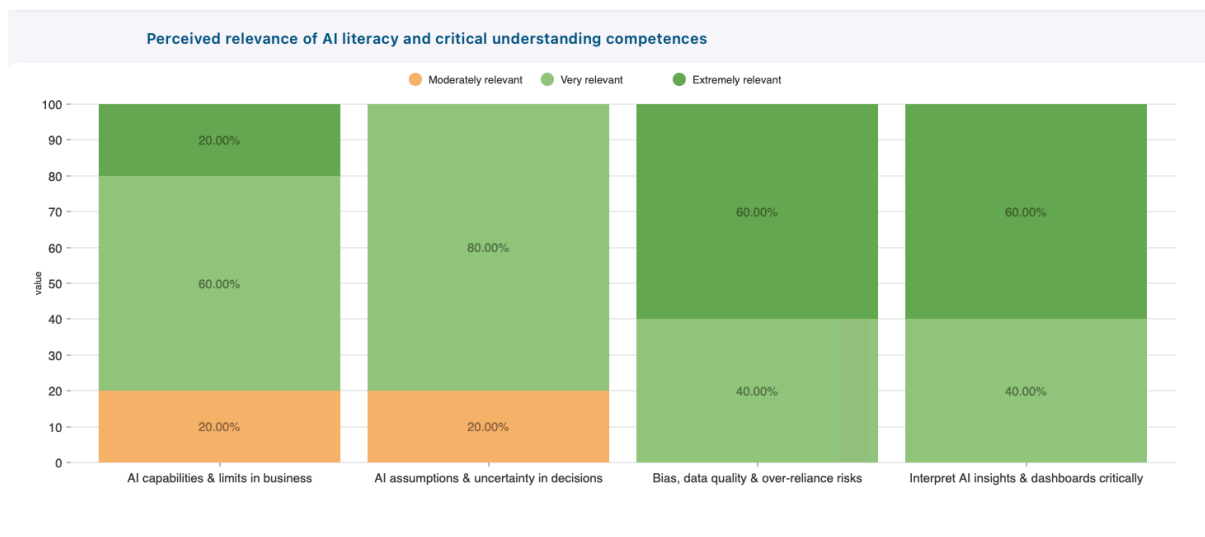
Course concept assessment. The concept is positively evaluated. Attractiveness receives 40% *quite a bit* and 40% *very much*. Perceived innovativeness shows 40% *very much*, 20% *quite a bit*, and 40% *somewhat*. Perceived need is more moderately distributed (40% *somewhat*, 40% *quite a bit*, 20% *very much*), though still positive overall.



Overall assessment of the course concept – Companies and Organisations profile

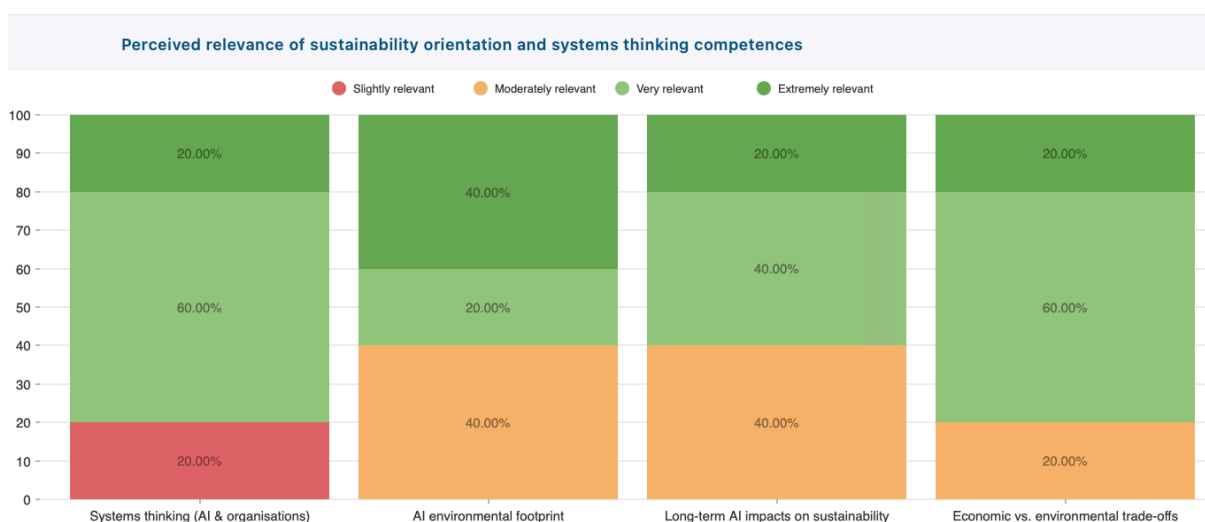
Competence domain evaluations. The Companies profile displays a governance-driven and application-oriented pattern across all five domains.

In *AI Literacy and Critical Understanding*, competences related to bias, data quality, and risks of over-reliance receive particularly strong support (60% *extremely relevant*). Critical interpretation of AI insights and dashboards is equally endorsed. Understanding AI assumptions and uncertainty in decisions is rated predominantly *very relevant* (80%). Organisations prioritise critical and risk-aware use of AI over purely technical familiarity.



Perceived relevance of AI literacy and critical understanding competences – Companies and Organisations profile

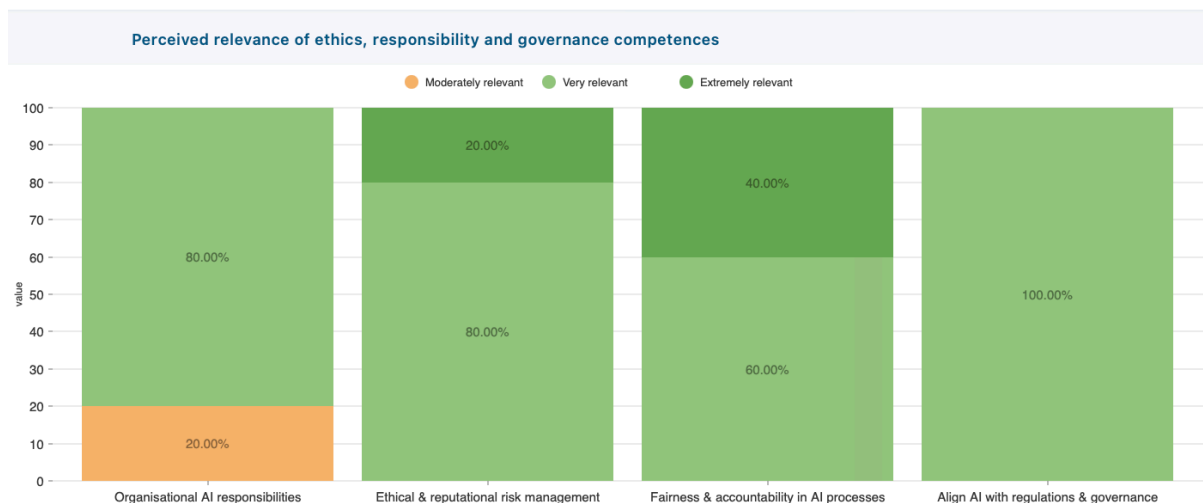
In *Sustainability Orientation and Systems Thinking*, systems thinking is rated 60% *very relevant* and 20% *extremely relevant*, though 20% consider it only *slightly relevant*, suggesting some variation in how systemic framing is perceived in organisational contexts. Economic-versus-environmental trade-offs receive strong endorsement (60% *very relevant*, 20% *extremely relevant*).



Perceived relevance of sustainability orientation and systems thinking competences – Companies and Organisations profile

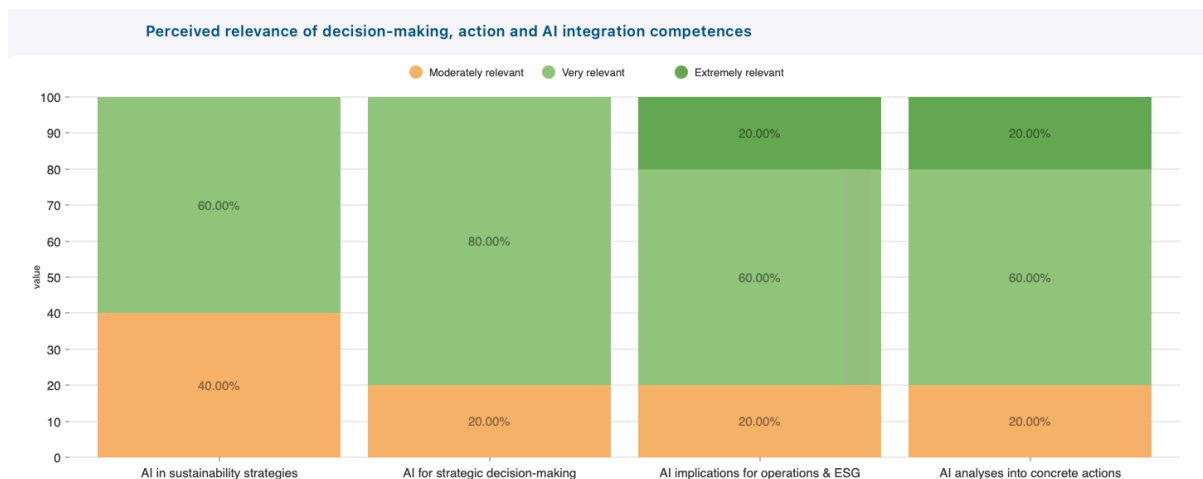
Ethics, Responsibility and Governance emerges as a central priority. Aligning AI with regulations and governance is rated 100% *very relevant*. Organisational AI responsibilities and

ethical/reputational risk management are predominantly *very relevant* (80%) or *extremely relevant*. Fairness and accountability also receive high endorsement (40% *extremely relevant*, 60% *very relevant*). Governance alignment clearly stands as a defining concern for this profile.



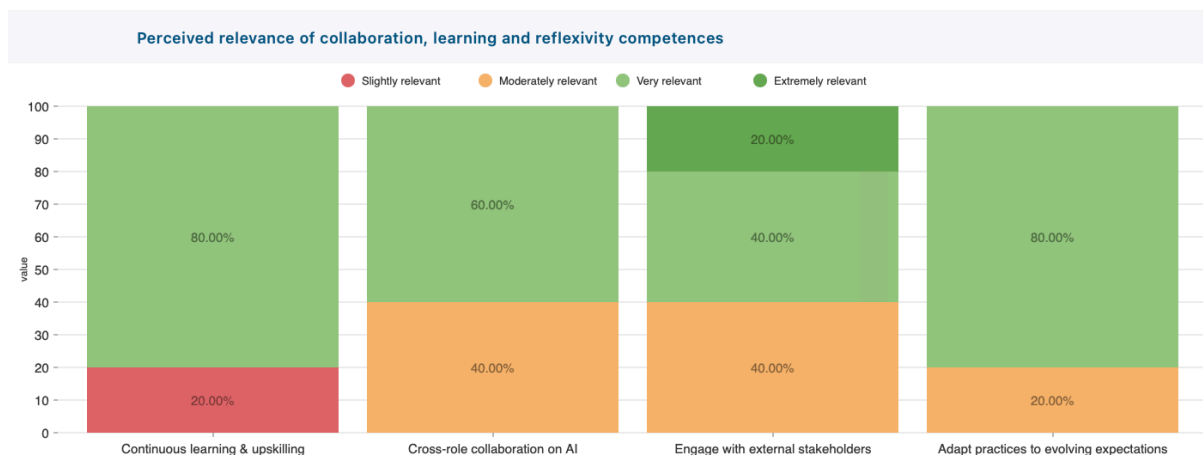
Perceived relevance of ethics, responsibility and governance competences – Companies and Organisations profile

In *Decision-Making, Action and AI Integration*, AI for strategic decision-making is rated 80% *very relevant*. Implications for operations and ESG, and translating AI analyses into concrete actions, receive balanced distributions between *very* and *extremely relevant*. AI in sustainability strategies shows slightly more moderate ratings (40% *moderately relevant*) but remains overall positively evaluated.



Perceived relevance of decision-making, action and AI integration competences – Companies and Organisations profile

Collaboration, Learning and Reflexivity shows particular emphasis on continuous learning: both continuous upskilling and adapting practices to evolving expectations are rated 80% *very relevant*. Cross-role collaboration and engagement with external stakeholders are positively evaluated, though with more moderate distributions.



Perceived relevance of collaboration, learning and reflexivity competences – Companies and Organisations profile

Open-ended responses reinforce the applied orientation. Respondents suggest that the programme should actively involve enterprises at different stages of ESG-related AI adoption, grounding the learning experience in concrete implementation cases and transitional experiences. This signals that the added value of the programme, for this profile, lies not only in conceptual framing but in structured engagement with real-world organisational practice.

8.5. Cross-Profile Patterns and Implications for Design

Four cross-cutting patterns emerge from the consultation results across all profiles, each with direct implications for the design recommendations presented in Section 2.

Strong perceived need for education at the AI-sustainability intersection. Respondents from academic and organisational contexts consistently recognise a gap in existing curricula and training offers. The integration of sustainability considerations into AI-related education is not perceived as optional or complementary, but as necessary. This validation is especially significant given the diversity of backgrounds represented in the consultation, and directly supports the RADAR-aim decision to position its micro-credential programme at this intersection (Section 3).

Convergent emphasis on governance, ethics, and critical AI literacy. Across all profiles, competences related to fairness, accountability, regulatory alignment, risk awareness, and the critical interpretation of AI outputs are consistently rated among the most relevant. Even in technically oriented profiles, responsibility and governance are positioned as structural elements of professional competence, not as peripheral themes. This pattern strengthens the inclusion of Ethics, Responsibility and Governance as one of the five core competence domains (Section 2.9) and supports embedding ethical and governance dimensions throughout the curriculum tiers (Section 2.7) rather than confining them to a dedicated module.

Sustainability competences widely supported, with profile-specific framing. Environmental footprint, long-term impacts, and trade-off management receive broad endorsement across profiles. However, the intensity and framing differ: technical stakeholders tend to frame sustainability through impact assessment and operational criteria; Social Sciences and Management stakeholders emphasise systemic framing and governance implications; Companies position sustainability in pragmatic and decision-oriented terms, linking it to risk

management, ESG integration, and regulatory compliance. These differences do not indicate divergence but rather complementary perspectives that reinforce the interdisciplinary rationale of the four-pathway structure (Section 2.1).

Demand for applied and practice-oriented learning formats. While the structural design of the programme is strongly validated across profiles, open-ended responses consistently call for the integration of case studies, simulations, real organisational examples, and opportunities to test concepts in applied contexts. Organisational respondents in particular highlight the importance of involving enterprises at different stages of AI adoption for sustainability. This signals that stakeholder expectations extend beyond conceptual alignment toward experiential and implementation-oriented learning, reinforcing the design recommendations on authentic assessment (Section 2.2) and supportive learning environments (Section 2.4).

In addition, qualitative inputs identify specific areas for strengthening: deeper treatment of risk assessment and data quality management, the environmental impacts of AI systems themselves, risks of over-reliance on AI, and broader geopolitical and international governance perspectives. These signals will inform the refinement of content priorities as the programme moves into the development phase (WP3).

8.6. Current Status and Next Steps

The results presented in Section 4.5 represent the first phase of the stakeholder consultation, conducted during WP2. The consultation will continue during WP3, with the objective of expanding the sample across all four profiles and partner countries, strengthening the evidence base for profiles with smaller samples (Engineering and Design, Companies and Organisations), and collecting targeted feedback on specific curriculum components as they are developed.

The first-phase results already provide a substantive validation layer for the design recommendations. The alignment between the four survey profiles and the four learner pathways described in Section 2.1 enables direct comparison between the competences deemed important by each stakeholder group and the learning outcomes proposed for their respective pathways. The cross-profile patterns identified in Section 8.5 confirm the structural soundness of the proposed programme architecture while highlighting areas where content priorities can be sharpened during course development. The full analysis of all consultation phases will be reported in this report.

9. Conclusion

Work Package 2 of the RADAR-aim project has conducted a comprehensive examination of the global landscape of sustainability education, identified the design standards and practices that shape contemporary offerings, assessed the suitability of existing frameworks for micro-credential development, and gathered stakeholder feedback to inform design recommendations. The resulting evidence base maps 345 programmes across 32 countries, analyses the content of 31 core AI-integration programmes, evaluates existing micro-credential frameworks, and incorporates input from four stakeholder profiles, thereby providing a robust foundation for the subsequent Develop and Adopt phases.

The key findings are clear: sustainability education has not meaningfully integrated AI competencies, despite growing evidence of AI's potential contributions to sustainability challenges and persistent labour market demand for professionals who can bridge these two domains. The AI integration deficit is structural and pervasive, affecting 85.5% of all programmes reviewed and 96.9% of emerging micro-credential offerings. This deficit exists not because quality teaching is impossible but because faculty expertise, curriculum development capacity, and institutional incentives have not yet aligned to address it.

However, the evidence also reveals pathways forward. Institutions that have developed core AI-integration programmes have converged on effective pedagogical approaches: hands-on practical work, industry engagement, and project-based assessment. Existing European micro-credential frameworks provide solid foundations for quality assurance, credit denomination, and digital recognition. Stakeholders, across AI specialists, engineering professionals, social scientists, and employers, validate both the need for AI-sustainability micro-credentials and the proposed design architecture.

The design recommendations presented in Section 6, grounded in the empirical analysis and stakeholder feedback, provide a blueprint for the RADAR-aim micro-credential development. These recommendations address the specific challenges identified in this report: defining learning outcomes that differentiate by learner profile, developing assessment strategies that explicitly evaluate interdisciplinary competences, creating modular structures that accommodate rapid content updates, and building in quality assurance proportionate to the micro-credential scope.

Work Package 2 establishes that the opportunity for innovation is substantial and the readiness for implementation is high. The Develop phase (Work Package 3) will translate these recommendations into concrete curriculum modules, learning environments, and quality assurance mechanisms. The Adopt phase (Work Package 4) will test these offerings with learners and institutions, refine them based on experience, and establish the conditions for broader institutional uptake.

References

Academic Literature

Rolnick, D., Donti, P.L., Kaack, L.H., Kochanski, K., Lacoste, A., Sankaran, K., Ross, A.S., Milojevic-Dupont, N., Jaques, N., Waldman-Brown, A., Luccioni, A.S., Maharaj, T., Sherwin, E.D., Mukkavilli, S.K., Kording, K.P., Gomes, C.P., Ng, A.Y., Hassabis, D., Platt, J.C., Creutzig, F., Chayes, J. & Bengio, Y. (2022). Tackling climate change with machine learning. *ACM Computing Surveys*, 55(2), 1–96. <https://doi.org/10.1145/3485128>

Vinuesa, R., Azizpour, H., Leite, I., Balaam, M., Dignum, V., Domisch, S., Felländer, A., Langhans, S.D., Tegmark, M. & Fuso Nerini, F. (2020). The role of artificial intelligence in achieving the Sustainable Development Goals. *Nature Communications*, 11(1), 233. <https://doi.org/10.1038/s41467-019-14108-y>

Labour Market and Industry Reports

Deloitte (2024). *Talent and Workforce Effects in the Age of AI*. Deloitte Insights.

Gartner (2024). Survey on generative AI deployment and skills requirements. Gartner Research.

World Economic Forum (2023). *The Future of Jobs Report 2023*. World Economic Forum. <https://www.weforum.org/publications/the-future-of-jobs-report-2023/>

European Policy and Quality Assurance Frameworks

CIMEA. *Methodology and Key Findings on Micro-credentials Recognition*. Italian Information Centre on Academic Mobility and Equivalence.

Council of the European Union (2022). Council Recommendation on a European approach to micro-credentials for lifelong learning and employability. *Official Journal of the European Union*, C 243/10.

European Commission (2015). *ECTS Users' Guide*. Publications Office of the European Union. <https://doi.org/10.2766/87192>

European Commission / EACEA / Eurydice (2020). *The European Higher Education Area in 2020: Bologna Process Implementation Report*. Publications Office of the European Union.

European Commission, Joint Research Centre (2022). DigComp 2.2: The Digital Competence Framework for Citizens: With new examples of knowledge, skills and attitudes. Publications Office of the European Union. <https://doi.org/10.2760/115376>

European Commission, Joint Research Centre (2024). *Micro-credentials in Higher Education*. JRC142086. Publications Office of the European Union.

European Training Foundation (2023). *Micro-credential Guidelines*. Available at: <https://www.etf.europa.eu>

European Training Foundation (2023). *Micro-Credentials: A Shared Understanding*. ETF Guidelines.

EADTU. Common Microcredentials Framework (CMF). Available at: <https://emc.eadtu.eu/cmfc/common-microcredential-framework-cmf>

QAA (2022). *Characteristics Statement: Micro-credentials*. UK Quality Assurance Agency for Higher Education.

Quality Assurance Agency for Higher Education (2014). *UK Quality Code for Higher Education, Part A: Setting and Maintaining Academic Standards*. QAA.

Programme Data

RADAR-aim Database: Postgraduate programmes in AI and sustainability (345 programmes, 32 countries). Internal project documentation.

RADAR-aim Database: In-depth curriculum analysis of 31 programmes with core AI integration. Internal project documentation.

Study.eu, mastersportal.com, education.com, and national academic databases (Portugal, Spain, Italy).

Appendix A: Programmes with Core AI

Programme Title	University	Country	Duration	Category
Master AI for Sustainable Technologies	Fachhochschule Salzburg GmbH	Austria	2 years	Information Technologies
MSc in Data Science for Sustainability	Modul University Vienna	Austria	2 years	Data Science
MSc in Sustainable Development, Management and Policy	Modul University Vienna	Austria	2 years	Policy & Management
MSc AI for Sustainable Innovation	Tomorrow University	Germany	2 years	Innovation
MSc Data Science for Sustainable Development	Tomorrow University of Applied Sciences	Germany	2 years	Data Science
MSc Sustainable Finance	Michael Smurfit Graduate Business School	Ireland	2 years	Finance
MSc in Statistics and Sustainability	Trinity College Dublin	Ireland	2 years	Statistics
MSc Transformative Sustainability	Bocconi University	Italy	2 years	Business & Sustainability
PGDip Destination Management: Sustainability, Experiences and AI	University of Pisa	Italy	1 year	Tourism & Hospitality
Master in Green Data Science	Instituto Superior de Agronomia	Portugal	2 years	Agriculture
MA Artificial Intelligence For Sustainable Societies	Erasmus Mundus	Several	2 years	Sustainable Societies

Programme Title	University	Country	Duration	Category
MSc in Data Science for Sustainability	National University of Singapore	Singapore	1 year	Data Science
MSc AI and Sustainable Development	Birmingham University	UK	1 year	Sustainable Development
MSc Data Science for Environmental Sustainability	Cardiff University	UK	1 year	Environmental Science
MSc Data Science and AI for Sustainability	Cranfield University	UK	1 year	Environmental Science
MSc Environmental Data Science and Machine Learning	Imperial College London	UK	1 year	Environmental Science
MSc Geo-Energy with Machine Learning and Data Science	Imperial College London	UK	1 year	Energy & Geoscience
MSc Data Science for Environmental Science	University of East Anglia	UK	1 year	Environmental Science
MSc Artificial Intelligence for Sustainable Development	University College London	UK	1 year	Sustainable Development
MSc Built Environment: Sustainable Heritage (Data Science)	University College London	UK	1 year	Heritage & Built Environment
MSc Applied Data Science (Environment and Sustainability)	University of Exeter	UK	1 year	Environmental Science
MSc Artificial Intelligence for the Environment	University of Exeter	UK	1 year	Environmental Science
MSc Environmental Data Science and Analytics	University of Leeds	UK	1 year	Environmental Science
MSc Data Science and Environmental Intelligence	University of Plymouth	UK	1 year	Environmental Science
MSc Climate Change and Artificial Intelligence (AI)	University of Reading	UK	1 year	Climate Science
MSc Environmental Sustainability and Data Science	University of Westminster	UK	1 year	Environmental Science
Master of Environmental Data Science (MEDS)	UC Santa Barbara Bren School	USA	1 year	Environmental Science
MS in Environmental Data Analytics	Unity Environmental University	USA	1 year	Environmental Science
MEng Engineering and Sustainable Technology Management	SRH University	Germany	2 years	Engineering

Programme Title	University	Country	Duration	Category
MSc Financial Data Analytics and Sustainable Finance	European University Cyprus	Cyprus	1 year	Finance
Master in Innovation and Research for Sustainability	ISEG, Universidade de Lisboa	Portugal	2 years	Innovation

Appendix B: Micro-Credential and Short-Course Programmes

Programme Title	Institution	Country
Micro-credential in Artificial Intelligence & Society	University of Graz	Austria
Postgraduate Course in AI for the Common Good	Vrije Universiteit Brussel (VUB) & Université libre de Bruxelles (ULB)	Belgium
Micro-credential in Future of Artificial Intelligence	University of Galway	Ireland
Micro-credential in Societal Impact of Artificial Intelligence	University of Galway	Ireland
Micro-credential in Data Analysis and Visualisation	University of Galway	Ireland
Micro-credential in Introduction to Artificial Intelligence	University of Galway	Ireland
Micro-credential in Machine Learning & Natural Language Processing	University of Galway	Ireland
Short-term Course in Fundamentals of Artificial Intelligence (MERIT)	Vilnius Tech	Lithuania
Executive Course in Artificial Intelligence & Machine Learning for Business	Bologna Business School	Italy
Micro-credential in Artificial Intelligence (in a Nutshell)	EU-CONEXUS Alliance	Spain, Croatia, Lithuania
Micro-credential in Artificial Intelligence Collection	University of Helsinki	Finland
University Expert Program in Artificial Intelligence	Universitat Ramon Llull (La Salle)	Spain

Programme Title	Institution	Country
Micro-credential in A Human-Centred Approach in AI Deployment	Aalto University Executive Education	Finland
Micro-certificate in Applied AI for Technical Innovation	Czech Technical University (CTU) Prague	Czech Republic
Short Course in Artificial Intelligence for Productivity	Australian Institute of Management (AIM)	Australia
Microcredential in Introduction to AI for Data Analytics and Forecasting	Australian Institute of Management (AIM)	Australia
Diploma of Artificial Intelligence	Australian Institute of Management (AIM)	Australia
Microcredentials Program in Artificial Intelligence	Purdue University	United States
Micro-accreditation in Smart Tourism	NOVA Information Management School (NOVA IMS)	Portugal
Micro-accreditation in Data Science for Hospitality & Tourism	NOVA Information Management School (NOVA IMS)	Portugal
Micro-credential in Driving Performance with AI and Analytics	Trinity College Dublin	Ireland
Micro-credential in Data Analytics and Artificial Intelligence	Media Design School	New Zealand
Micro-credential in Practice AI with Programming	Institute of Applied Technology	Australia
Micro-credential in Artificial Intelligence Ethics	Athabasca University	Canada
Micro-credential in Artificial Intelligence for Business Leaders	Open Polytechnic	New Zealand
Micro-credential in The Academic Applications of AI (AAAI) for Faculty	California State University	United States
Micro-credential Program in Practical Utilisation of AI	St. Francis Xavier University	Canada
Micro-credentials in Artificial Intelligence	University of Malta	Malta
Micro-credential in Applied Artificial Intelligence	Georgetown University	United States
Micro-credential in Advanced AI for Economic and Business Analysis	Empire State University	United States

Programme Title	Institution	Country
Micro-credential in Academic Applications of Artificial Intelligence	SDSU Global Campus	United States
Micro-credential in Introduction to Generative Artificial Intelligence	Open Polytechnic	New Zealand

Appendix C: Stakeholder Consultation Questionnaires

This appendix reproduces the four profile-specific questionnaires used in the stakeholder consultation (Section 8). All four instruments share a common structure organised in two sections: (i) assessment of the course concept, structure, and topic relevance; and (ii) evaluation of competence statements across five domains. Items are adapted to the perspective of each target group while maintaining structural consistency to support cross-profile comparison.

C.1. AI and Data Science Profile

Section 1 – Courses and Topics

Please think about a course on AI and Sustainability aimed at people with a strong technical background (e.g. AI, data science, computer science, or information technology). This course is designed to build on existing AI expertise and orient it towards sustainability challenges.

Please answer the following questions with this course idea in mind.

Course structure

The course on AI and Sustainability is composed of three main parts:

- Basic knowledge (e.g. sustainability fundamentals and key sustainability challenges)
- Advanced knowledge (e.g. systems thinking, critical reflection, interdisciplinary perspectives)
- Domain-specific knowledge (e.g. AI methods applied to sustainability challenges, data-driven sustainability analysis, impact-oriented AI applications)

Adequacy of the course structure

How adequate do you consider the overall course structure described above?

Response scale: 1 = Not appropriate at all; 5 = Extremely appropriate (Not sure / Cannot judge)

Do you have any suggestions to improve the course structure? *Open text response*

Topics

How relevant do you consider the following topics for the basic and advanced knowledge components of the course?

- Introduction to sustainability concepts and challenges
- Ethics and responsible use of AI (ethical principles, accountability, transparency, risk awareness)

- c) Sustainable use of AI (environmental, social, and economic impacts of AI systems and AI-enabled decisions)
- d) Use of Artificial Intelligence to support sustainability-oriented practices (overview of typical use cases and potential across different sectors)
- e) Transversal knowledge areas for AI and sustainability (systems thinking, critical thinking, futures thinking)

Response scale: 1 = Not relevant at all; 5 = Extremely relevant (Not sure / Cannot judge)

Do you have any suggestions to improve the list of topics? *Open text response*

Overall assessment of the course concept

- How attractive do you find a course structured and designed in this way?
- To what extent do you think a course like this is needed in the current AI education landscape?
- How innovative do you find this course concept compared to existing AI-related courses?

Response scale: 1 = Not at all; 5 = Very much (Not sure / Cannot judge)

Section 2 – Competences for AI and Sustainability

Keeping in mind people with strong technical backgrounds who wish to orient their expertise towards AI and Sustainability, please indicate the relevance of the competences listed below.

Response scale: 1 = Not relevant at all; 5 = Extremely relevant (Not sure / Cannot judge)

AI Literacy and Critical Understanding

- Ability to critically assess the assumptions, limitations, and uncertainty of AI models and data when applied to sustainability-related problems
- Ability to interpret AI outputs in a critical and informed way, avoiding over-reliance on automated results
- Ability to recognise bias, data quality issues, and methodological limitations in AI systems used in sustainability contexts

Sustainability Orientation and Systems Thinking

- Awareness of the environmental footprint of digital and AI systems themselves (e.g. energy use, data infrastructure, resource consumption)
- Ability to apply systems thinking to understand interactions between AI systems and environmental, social, and economic systems
- Ability to frame sustainability-related problems appropriately before designing or deploying AI-based solutions
- Ability to consider long-term and unintended impacts of AI systems on society and the environment

Ethics, Responsibility and Governance

- Awareness of fairness, inclusion, and potential biases embedded in AI systems and data
- Ability to identify ethical issues related to the design, development, and deployment of AI systems
- Ability to make responsible choices when developing or deploying AI solutions that affect sustainability outcomes
- Ability to understand and engage with ethical and governance frameworks relevant to AI and sustainability

Decision-Making, Action, and AI Integration

- Ability to translate technical AI expertise into concrete actions that support sustainability transitions
- Ability to integrate AI-based insights into sustainability-oriented decision-making processes
- Ability to assess trade-offs between performance, efficiency, and sustainability outcomes when using AI
- Ability to combine AI-based analysis with contextual and domain-specific knowledge

Collaboration, Learning, and Reflexivity

- Ability to collaborate effectively with non-technical stakeholders (e.g. planners, policymakers, managers, civil society actors) on sustainability-oriented AI projects
- Ability to communicate AI-based results, limitations, and implications clearly to diverse audiences
- Ability to critically reflect on one's professional role and responsibilities as an AI expert working on sustainability challenges
- Ability to adapt one's AI expertise to evolving sustainability challenges, societal expectations, and regulatory contexts

Are there additional competences you consider particularly relevant? *Open text response*

Do you have other ideas or concerns to share about a course on AI and Sustainability for people with a strong technical background? *Open text response*

Demographics

1. Your current role (select all that apply): Bachelor student; Master student; PhD/Doctoral researcher; Lifelong learner; Educator/Lecturer/Professor; Instructor/Trainer; Instructional designer/Learning experience designer; Researcher (non-teaching); Other
2. Your main field(s) of study or expertise (select up to two): Artificial Intelligence; Data Science/Analytics; Computer Science/IT; Engineering; Other
3. Your level of experience in this field: Less than 2 years; 2-5 years; 6-10 years; More than 10 years; Prefer not to say

4. Your current level of exposure to sustainability topics in relation to AI: I mainly study or work in AI/data science, with little or no exposure to sustainability topics; I have occasional exposure to sustainability-related issues in AI-related studies or activities; I regularly engage with sustainability-related topics in my AI-related studies or work; AI and sustainability are strongly integrated in my current studies or professional activities; Prefer not to say

C.2. Engineering and Design Profile

Section 1 – Courses and Topics

Please think about a course on AI and Sustainability aimed at people with a strong background in engineering, architecture, planning, modelling, design, or related technical fields, with an orientation towards sustainability and related challenges. This course is designed for people who want to use AI as a supporting tool rather than developing AI systems themselves.

Please answer the following questions with this course idea in mind.

Course structure

This course on AI and Sustainability is composed of three main parts:

- Basic knowledge (e.g. fundamentals of AI and GenAI)
- Advanced knowledge (e.g. AI literacy, responsible use of AI, interpretation of AI outputs, integration of AI into decision-making)
- Domain-specific knowledge (e.g. AI-supported modelling, simulation, planning)

Adequacy of the course structure

How adequate do you consider the overall course structure described above?

Response scale: 1 = Not appropriate at all; 5 = Extremely appropriate (Not sure / Cannot judge)

Do you have any suggestions to improve the course structure? *Open text response*

Topics

How relevant do you consider the following topics for the basic and advanced knowledge components of the course?

- Introduction to Artificial Intelligence and Generative AI (key concepts, capabilities, and limitations relevant for technical and design contexts)
- Ethics and responsible use of AI (ethical principles, accountability, transparency, risk awareness)
- Sustainable use of AI (environmental, social, and economic impacts of AI systems and AI-enabled decisions)
- Use of Artificial Intelligence to support sustainability-oriented practices (overview of typical use cases and potential in technical and design contexts)
- Transversal knowledge areas for AI and sustainability (AI literacy concepts, critical understanding of AI use, interpretation of AI outputs, principles of responsible AI as a normative and conceptual reference framework)

Response scale: 1 = Not relevant at all; 5 = Extremely relevant (Not sure / Cannot judge)

Do you have any suggestions to improve the list of topics? *Open text response*

Overall assessment of the course concept

- How attractive do you find a course structured and designed in this way?
- To what extent do you think a course like this is needed in the current AI education landscape?
- How innovative do you find this course concept compared to existing AI-related courses?

Response scale: 1 = Not at all; 5 = Very much (Not sure / Cannot judge)

Section 2 – Competences for AI and Sustainability

Keeping in mind people with strong technical backgrounds in engineering and design fields, with an orientation towards sustainability and related challenges and who wish to use AI as a supporting tool, please indicate the relevance of the competences listed below.

Response scale: 1 = Not relevant at all; 5 = Extremely relevant (Not sure / Cannot judge)

AI Literacy and Critical Understanding

- Ability to understand basic principles of how AI systems work (e.g. data inputs, models, outputs) in engineering and design contexts
- Ability to understand the purpose, assumptions, and limits of AI tools used in modelling, simulation, analysis, or design tasks
- Ability to critically interpret AI-generated data, simulations, or recommendations used to support technical and design decisions
- Ability to recognise uncertainty, limitations, and potential bias in AI-supported analyses

Sustainability Orientation and Systems Thinking

- Awareness of the environmental footprint of digital and AI systems themselves (e.g. energy use, data infrastructure, resource consumption)
- Ability to apply systems thinking to understand interactions between AI-supported design or engineering solutions and environmental, social, and economic systems
- Ability to consider long-term and unintended sustainability impacts of AI-supported technical or design decisions
- Ability to frame sustainability-related technical problems appropriately before relying on AI-based tools or outputs

Ethics, Responsibility, and Governance

- Awareness of fairness, inclusion, and potential biases embedded in AI tools and data used for technical or design purposes
- Ability to identify ethical issues related to the use of AI in engineering, planning, or design contexts

- Ability to make informed and responsible choices when relying on AI outputs that influence sustainability-related decisions
- Ability to understand relevant ethical principles and governance considerations related to AI use in professional practice

Decision-Making, Action, and AI Integration

- Ability to integrate AI-based insights into engineering, planning, or design decision-making processes
- Ability to combine AI-supported analysis with professional judgement, contextual knowledge, and stakeholder requirements
- Ability to use AI as a support tool to improve sustainability performance in technical or design projects
- Ability to assess trade-offs between technical performance, feasibility, and sustainability outcomes when using AI

Collaboration, Learning, and Reflexivity

- Ability to collaborate effectively with AI and data specialists as well as non-technical stakeholders on sustainability-oriented projects
- Ability to communicate AI-supported results, assumptions, and limitations clearly to diverse audiences (e.g. clients, decision-makers, communities)
- Ability to critically reflect on one's professional responsibilities when using AI in sustainability-oriented engineering and design contexts
- Ability to adapt one's professional practice to evolving sustainability challenges, societal expectations, and regulatory contexts related to AI

Are there additional competences you consider particularly relevant? *Open text response*

Do you have other ideas or concerns to share about this course on AI and Sustainability for people with strong technical backgrounds in engineering and design fields? *Open text response*

Demographics

1. Your current role (select all that apply): Bachelor student; Master student; PhD/Doctoral researcher; Lifelong learner; Educator/Lecturer/Professor; Instructor/Trainer; Instructional designer/Learning experience designer; Researcher (non-teaching); Other
2. Your main field(s) of study or expertise (select up to two): Engineering (e.g. civil, environmental, energy, industrial); Architecture/Urban or spatial planning; Design (industrial, product, service, systems); Modelling/Simulation; Sustainability/Environmental studies (e.g. sustainable design, environmental engineering); Other
3. Your level of experience in this field: Less than 2 years; 2-5 years; 6-10 years; More than 10 years; Prefer not to say

4. Your current level of exposure to sustainability topics in relation to AI: I mainly study or work in engineering or design for sustainability, with little or no engagement with AI; I have occasional exposure to AI tools, methods, or outputs in engineering or design contexts; I regularly engage with AI-supported tools or models in sustainability-oriented engineering or design studies or activities; AI-supported analysis or design is a central part of my current studies or professional activities; Prefer not to say

C.3. Social Sciences and Management Profile

Section 1 – Courses and Topics

Please think about a course on AI and Sustainability aimed at people with a strong background in social sciences, management, law, economics, humanities, or related fields, with an orientation towards sustainability and related challenges. This course is designed for people who want to engage with Artificial Intelligence from a non-technical perspective.

Please answer the following questions with this course idea in mind.

Course structure

This course on AI and Sustainability is composed of three main parts:

- Basic knowledge (e.g. basic concepts of AI and GenAI, introduction to sustainability and AI-related challenges)
- Advanced knowledge (e.g. ethical and regulatory understanding of AI, critical interpretation of AI outputs)
- Domain-specific knowledge (e.g. AI-informed decision-making, policy analysis)

Adequacy of the course structure

How adequate do you consider the overall course structure described above?

Response scale: 1 = Not appropriate at all; 5 = Extremely appropriate (Not sure / Cannot judge)

Do you have any suggestions to improve the course structure? *Open text response*

Topics

How relevant do you consider the following topics for the basic and advanced knowledge components of the course?

- a) Introduction to Artificial Intelligence and Generative AI (key concepts, capabilities, and limitations from a non-technical perspective)
- b) Ethics and responsible use of AI (ethical principles, accountability, transparency, risk awareness)
- c) Sustainable use of AI (environmental, social, and economic impacts of AI systems and AI-enabled decisions)
- d) Use of Artificial Intelligence to support sustainability-oriented practices (overview of typical use cases and potential in social, organisational, and policy contexts)

- e) Transversal knowledge areas for AI and sustainability (AI literacy concepts, critical understanding of AI and GenAI use, interpretation of AI and GenAI outputs, principles of responsible AI as a normative and conceptual reference framework)

Response scale: 1 = Not relevant at all; 5 = Extremely relevant (Not sure / Cannot judge)

Do you have any suggestions to improve the list of topics? *Open text response*

Overall assessment of the course concept

- How attractive do you find a course structured and designed in this way?
- To what extent do you think a course like this is needed in the current AI education landscape?
- How innovative do you find this course concept compared to existing AI-related courses?

Response scale: 1 = Not at all; 5 = Very much (Not sure / Cannot judge)

Section 2 – Competences for AI and Sustainability

Keeping in mind people with strong backgrounds in social sciences and related fields, with an orientation towards sustainability and related challenges and engaging with AI from a non-technical perspective, please indicate the relevance of the competences listed below.

Response scale: 1 = Not relevant at all; 5 = Extremely relevant (Not sure / Cannot judge)

AI Literacy and Critical Understanding

- Awareness of uncertainty, limitations, and potential bias in AI-supported analyses and outputs
- Ability to understand basic principles of how AI systems work (e.g. data inputs, automated decision-making, outputs) in sustainability-related contexts
- Ability to understand the purpose, assumptions, and limits of AI systems used in policy, organisational, economic, or societal settings
- Ability to critically interpret AI-generated information and recommendations used in sustainability-related decision-making processes

Sustainability Orientation and Systems Thinking

- Awareness of the environmental and social footprint of digital and AI systems
- Ability to apply systems thinking to understand interactions between AI systems and environmental, social, economic, and institutional systems
- Ability to consider long-term and unintended impacts of AI use on society, governance processes, and sustainability transitions
- Ability to frame sustainability-related societal or organisational problems appropriately before relying on AI-supported analyses

Ethics, Responsibility, and Governance

- Ability to identify ethical issues related to the use of AI systems in social, organisational, and policy contexts
- Ability to assess fairness, accountability, transparency, and responsibility in AI-supported decisions
- Ability to understand legal, regulatory, and governance frameworks relevant to AI and sustainability
- Ability to analyse social impacts, power relations, and distributional effects of AI systems in sustainability transitions

Decision-Making, Action, and AI Integration

- Ability to use AI-generated insights to support informed decision-making in sustainability-related organisational, policy, or governance contexts
- Ability to assess trade-offs and implications of AI-supported decisions for different stakeholders and sustainability goals
- Ability to integrate AI-based evidence with qualitative judgement, contextual knowledge, and societal considerations
- Ability to contribute to the design or evaluation of AI-informed policies, strategies, or organisational practices

Collaboration, Learning, and Reflexivity

- Ability to collaborate with technical experts, policymakers, managers, and other stakeholders on AI and sustainability issues
- Ability to communicate AI-related insights, assumptions, and limitations clearly to diverse audiences
- Ability to reflect critically on one's professional role and responsibility when engaging with AI in sustainability-oriented contexts
- Ability to adapt one's knowledge and practice to evolving AI-related societal challenges, sustainability priorities, and regulatory developments

Are there additional competences you consider particularly relevant? *Open text response*

Do you have other ideas or concerns to share about a course on AI and Sustainability for people with strong backgrounds in social sciences and related fields? *Open text response*

Demographics

1. Your current role (select all that apply): Bachelor student; Master student; PhD/Doctoral researcher; Lifelong learner; Educator/Lecturer/Professor; Instructor/Trainer; Instructional designer/Learning experience designer; Researcher (non-teaching); Other
2. Your main field(s) of study or expertise (select up to two): Social Sciences; Business/Management; Economics; Law/Legal studies; Public policy/Governance; Humanities; Sustainability/Environmental studies; Other

3. Your level of experience in this field: Less than 2 years; 2-5 years; 6-10 years; More than 10 years; Prefer not to say
4. Your current level of exposure to sustainability topics in relation to AI: I mainly study or work in sustainability-related contexts, with little or no direct engagement with AI; I occasionally engage with AI-related topics from a governance, policy, or decision-making perspective; I regularly engage with AI-related outputs, cases, or discussions in sustainability-oriented organisational or societal contexts; AI-related issues (e.g. ethics, regulation, societal impact) are central to my current studies or professional activities; Prefer not to say

C.4. Companies and Organisations Profile

Section 1 – Courses and Topics

Please think about an ideal course on AI and Sustainability aimed at companies or organisations engaged in one or more sustainability-oriented activities and interested in using Artificial Intelligence to support and strengthen their sustainability goals. This course is designed for organisations that wish to engage with Artificial Intelligence from a strategic, organisational, and responsible adoption perspective, rather than from a technical development standpoint.

Please answer the following questions with this course idea in mind.

Course structure

This course on AI and Sustainability is composed of three main parts:

- Basic knowledge (e.g. shared foundational concepts linking AI and sustainability in organisational contexts, alignment of AI concepts with existing sustainability strategies, common terminology)
- Advanced knowledge (e.g. responsible AI adoption, strategic thinking, systems thinking applied to organisational sustainability challenges)
- Domain-specific knowledge (e.g. AI applications for sustainability strategy, organisational decision-making, operational and ESG-related optimisation)

Adequacy of the course structure

How adequate do you consider the overall course structure described above?

Response scale: 1 = Not appropriate at all; 5 = Extremely appropriate (Not sure / Cannot judge)

Do you have any suggestions to improve the course structure? *Open text response*

Topics

How relevant do you consider the following topics for the basic and advanced knowledge components of the course?

- a) Introduction to sustainability concepts and challenges
- b) Introduction to Artificial Intelligence and Generative AI (key concepts, capabilities, and limitations relevant for organisations)

- c) Ethics and responsible use of AI (ethical principles, accountability, transparency, risk awareness)
- d) Sustainable use of AI (environmental, social, and economic impacts of AI systems and AI-enabled decisions)
- e) Use of Artificial Intelligence to support sustainability-oriented organisational practices (overview of typical use cases and potential, e.g. strategy, operations, ESG decision-making and governance)
- f) Transversal knowledge areas for AI and sustainability: AI literacy concepts, critical understanding of AI use, interpretation of AI outputs, principles of responsible AI as a normative and conceptual reference framework
- g) Transversal knowledge areas for AI and sustainability: systems thinking, critical thinking, futures thinking

Response scale: 1 = Not relevant at all; 5 = Extremely relevant (Not sure / Cannot judge)

Do you have any suggestions to improve the list of topics? *Open text response*

Overall assessment of the course concept

- How attractive do you find a course structured and designed in this way?
- To what extent do you think a course like this is needed in the current AI education landscape?
- How innovative do you find this course concept compared to existing AI-related courses?

Response scale: 1 = Not at all; 5 = Very much (Not sure / Cannot judge)

Section 2 – Competences for AI and Sustainability

Keeping in mind organisations engaged in sustainability-oriented activities that use Artificial Intelligence to support their sustainability goals, please indicate the relevance of the competences listed below.

Response scale: 1 = Not relevant at all; 5 = Extremely relevant (Not sure / Cannot judge)

AI Literacy and Critical Understanding

- Awareness of potential bias, data quality issues, and over-reliance risks in AI-supported business decisions
- Ability to understand what AI systems can and cannot do in sustainability-related business and organisational contexts
- Ability to understand the assumptions, limitations, and uncertainty of AI tools used in organisational decision-making
- Ability to critically interpret AI-generated insights, recommendations, and dashboards used to support sustainability strategies

Sustainability Orientation and Systems Thinking

- Awareness of the environmental footprint of digital and AI systems themselves (e.g. energy use, data infrastructure)
- Ability to apply systems thinking to understand interactions between AI adoption, organisational processes, and environmental and social sustainability outcomes
- Ability to assess long-term and unintended impacts of AI-enabled decisions on sustainability performance and value creation
- Ability to consider trade-offs between economic objectives, environmental performance, and social responsibility when adopting AI

Ethics, Responsibility, and Governance

- Awareness of organisational responsibilities related to responsible AI use and sustainability commitments
- Ability to identify and manage ethical, social, and reputational risks related to the use of AI in organisational contexts
- Ability to ensure fairness, transparency, and accountability in AI-supported organisational processes
- Ability to align AI adoption with relevant ethical principles, regulatory requirements, and governance frameworks

Decision-Making, Action, and AI Integration

- Ability to integrate AI-supported insights into organisational sustainability strategies and business models
- Ability to use AI to support strategic decision-making related to sustainability goals
- Ability to assess the organisational implications of AI adoption for operations, performance measurement, and ESG reporting
- Ability to translate AI-supported analyses into concrete actions that support sustainability objectives

Collaboration, Learning, and Reflexivity

- Ability to foster collaboration between technical and non-technical roles within the organisation on AI and sustainability initiatives
- Ability to engage with external stakeholders (e.g. consultants, partners, regulators) on AI and sustainability issues
- Ability to support continuous learning and upskilling on AI and sustainability within the organisation
- Ability to reflect critically on organisational practices and adapt them to evolving AI-related and sustainability-related expectations

Are there additional competences you consider particularly relevant? *Open text response*

Do you have other ideas or concerns to share about a course on AI and Sustainability for organisations engaged in sustainability-oriented activities? *Open text response*

Demographics

1. Your current professional role (select all that apply): Executive management/Senior leadership; Sustainability/ESG-related role; Innovation/Strategy; Digital, data, or AI-related role; HR/Training/Workforce development; Operations/Project or programme management; External expert/Consultant/Advisor; Other
2. Main sector(s) of activity of the organisation (select up to two): Energy production, distribution, or energy management; Utilities (water services, waste management, recycling); Manufacturing/Industrial production; Construction, real estate, or infrastructure; Mobility, transport, or logistics; Agri-food and food systems; Environmental services and monitoring; Sustainability, ESG, or environmental consulting; Digital, IT, or technology services supporting sustainability; Public sector or public-owned organisations; Non-profit or civil society organisations working on sustainability; Other
3. Your level of experience in your current role: Less than 2 years; 2-5 years; 6-10 years; More than 10 years; Prefer not to say
4. Size of the organisation: Micro or small organisations; Medium-sized organisations; Large organisations; A mix of different sizes; Prefer not to say
5. Current stage of AI adoption of the organisation: No current use of AI, but interest in adoption; Initial or pilot use of AI in sustainability-related activities; AI is used in specific functions or projects; AI is strategically integrated across multiple activities; Prefer not to say

End of Report