# Report WP2-A2:

Consolidated list of desired ILOs

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**Result**

Report on the consolidated list of the desired Intended Learning Outcomes for TAI MOOC on AI

**Related to**

WP2-A2: The definition of the ILOs each partner wants to achieve with the teaching material developed within this project

**Statement of originality**

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**Note**

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# 1. Introduction

Work Package 2 - Activity 2 (WP2-A2) focuses on the definition of the Intended Learning Outcomes (ILOs) that partner institutions aim to achieve through the AI teaching materials developed within the TAI project. Building on the evidence gathered in WP2-A1, this activity shifts the perspective from analysing the current state of AI education to articulating a shared, forward-looking vision of competencies that learners should develop. The primary purpose of WP2-A2 is therefore to establish a clear, measurable and harmonised set of desired ILOs that will guide the design of MOOCs and other educational resources within the project. By defining these outcomes collaboratively across all partners, the project ensures that future teaching materials are not only aligned with institutional needs but also coherent at the consortium level.

The work presented in this report is directly grounded in the findings of WP2-A1, which provided a comprehensive analysis of 94 AI/ML-related courses and their associated ILOs across partner institutions. That analysis revealed a consistent pattern: while the consortium demonstrates strong coverage of classical machine learning concepts—particularly supervised learning, data preparation and evaluation—significant gaps remain in modern learning paradigms, deployment-oriented skills, industrial applications and responsible AI topics. Additionally, WP2-A1 highlighted substantial variability in how ILOs are formulated, including inconsistent structure, frequent use of non-measurable verbs, and the prevalence of compound outcomes that are difficult to assess. These findings provide both the motivation and the foundation for WP2-A2, which aims to address these shortcomings through a systematic and standardised approach to outcome definition.

Within this context, Intended Learning Outcomes play a central role in AI curriculum design. Unlike traditional content-based approaches, which emphasise what is taught, ILOs focus on what learners are expected to know, understand and be able to do upon completion of a course or module. Properly formulated ILOs serve as the backbone of outcome-based education: they guide the selection of teaching methods, inform the design of assessments, and enable comparability across courses and institutions. In the rapidly evolving field of artificial intelligence—where new methods, tools and societal implications emerge continuously—well-defined ILOs are particularly important for ensuring that educational offerings remain relevant, practical and aligned with industry and regulatory expectations. Moreover, aligning ILOs with Bloom's taxonomy enables a structured progression of cognitive complexity, supporting the development of higher-order skills such as analysis, evaluation and creation, which are essential for modern AI practitioners.

This report presents the process and results of defining a consolidated set of desired ILOs for the TAI project. Following this introduction, the report outlines the methodological framework used to derive and standardise ILOs, including guiding principles and formulation rules. It then synthesises key insights from the WP2-A1 analysis to identify priority areas for development. Building on this foundation, the report introduces a competence framework for AI education and defines thematic categories of desired ILOs. Contributions from partner institutions are integrated and harmonised into a unified set of outcomes, which are then mapped to Bloom's taxonomy and key competence domains. The report culminates in the definition of a consolidated set of desired ILOs that will serve as the foundation for the next activity (WP2-A3), where these ILOs will be further analysed, categorised and translated into the educational structure of the project.

The University of Ljubljana (UNILJ) is the leading organization and coordinator for this work package.

# 2. Methodological framework for ILO definition

This section presents the approach used to define the desired Intended Learning Outcomes (ILOs) in WP2-A2. The methodology builds on the results of WP2-A1, incorporates partner inputs, and addresses identified curricular gaps. Its purpose is to ensure that the defined ILOs are clear, measurable, and aligned across all partner institutions while reflecting current and emerging needs in AI education.

## 2.1 Input sources

The definition of desired Intended Learning Outcomes (ILOs) in WP2-A2 is grounded in a combination of empirical evidence, partner contributions and strategic gap analysis. Three primary input sources were used to ensure that the resulting ILO framework is both evidence-based and aligned with the real needs of AI education across the consortium.

**The first and most comprehensive input source is the WP2-A1 analysis of existing AI/ML courses and their associated ILOs**. This analysis covered 94 courses across all partner institutions and provided a detailed overview of current teaching practices, topic coverage and outcome formulation. It enabled the identification of strengths—such as the widespread presence of supervised learning, data preparation and evaluation techniques—as well as systemic weaknesses, including limited coverage of modern AI paradigms, deployment workflows and responsible AI topics. In addition, the analysis of ILO structure revealed inconsistencies in wording, lack of standardisation and frequent use of non-measurable or compound outcomes. These findings form the empirical baseline for WP2-A2 and ensure that the proposed ILOs are not defined in isolation, but as a direct response to the current state of AI education within the consortium.

**The second key input consists of partner-specific ILO datasets collected from the analysed syllabi and supporting documents**. These datasets provide granular insight into how individual institutions articulate learning outcomes across different courses, domains and study levels. They reflect diverse academic traditions, disciplinary focuses and levels of maturity in AI education. Importantly, they also capture the range of verbs, competencies and cognitive levels currently used in practice. By systematically reviewing and comparing these ILOs, WP2-A2 is able to extract common patterns, identify best practices and detect redundancies or omissions. This bottom-up perspective ensures that the consolidated ILO framework remains realistic, grounded in actual teaching experience and representative of all partner institutions.

**The third input source is the set of curricular gaps identified through the cross-institution analysis conducted in WP2-A1**. These gaps highlight areas where current curricula fall short of contemporary AI education requirements. Key deficiencies include limited exposure to advanced learning paradigms such as transfer learning and self-supervised learning, insufficient focus on deployment and model lifecycle management practice, lack of application-oriented learning in industrial contexts, and inconsistent integration of ethical, legal and societal considerations. Furthermore, the relatively low presence of explainability and robustness topics points to a misalignment with emerging regulatory expectations, particularly within the European context. These identified gaps serve as a strategic guide for WP2-A2, ensuring that the newly defined ILOs do not merely reflect existing practices, but actively address missing competencies and support the development of a more complete, modern and responsible AI curriculum.

By combining these three input sources—empirical analysis, partner contributions and gap-driven priorities—WP2-A2 establishes a robust foundation for defining a coherent and future-oriented set of Intended Learning Outcomes.

## 2.2 Principles for defining ILOs

The definition of desired Intended Learning Outcomes (ILOs) in WP2-A2 is guided by a set of core principles that ensure the outcomes are clear, consistent, measurable and aligned with both educational best practices and the needs of modern AI curricula. These principles also address the shortcomings identified in WP2-A1, particularly the lack of standardisation and the frequent use of vague or compound outcome statements.

**Outcome-based education approach**

The ILOs are formulated following the principles of outcome-based education, where the emphasis is placed on what learners are expected to achieve upon completion of a course or module. Instead of focusing on content delivery, this approach prioritises learner performance and competencies. It ensures that teaching activities, learning materials and assessment methods are all aligned with clearly defined outcomes. This is particularly important in AI education, where students must not only understand theoretical concepts but also be able to apply, evaluate and design AI solutions in practical contexts..

**Alignment with Bloom's taxonomy**

All ILOs are aligned with Bloom's taxonomy to ensure a structured progression of cognitive complexity. The taxonomy provides a well-established framework for categorising learning outcomes according to levels such as remember, understand, apply, analyse, evaluate and create. In WP2-A2, particular emphasis is placed on higher-order cognitive levels (analyse, evaluate, create), reflecting the need for graduates to critically assess AI systems, design solutions and solve complex real-world problems. The use of clearly defined action verbs from Bloom’s taxonomy also supports consistency in outcome formulation and facilitates comparison across institutions.

**Measurability and assessability**

A key requirement for all ILOs is that they are measurable and assessable. Each outcome must be formulated in a way that allows learner achievement to be clearly evaluated through appropriate assessment methods. This requires the use of precise, action-oriented verbs and the avoidance of vague expressions such as “understand” or “be familiar with,” unless they are supported by observable performance indicators. Furthermore, each ILO should represent a single, clearly defined learning objective to ensure that it can be directly linked to specific assessment tasks. This principle addresses one of the main issues identified in WP2-A1, where many ILOs were compound or difficult to assess in practice.

Together, these principles provide a consistent framework for defining high-quality ILOs that support effective teaching, transparent assessment and alignment across the consortium.

## 2.3 Standardized ILO formulation rules

To ensure clarity, consistency and comparability across all partner institutions, WP2-A2 adopts a set of standardized rules for formulating Intended Learning Outcomes (ILOs). These rules are directly informed by the findings of WP2-A1, where significant variability was observed in ILO structure, wording and cognitive focus. In many cases, outcomes were expressed as long, compound sentences, included multiple actions, or relied on vague verbs that made them difficult to assess. The following rules aim to eliminate these issues and establish a common standard for high-quality ILO design.

**Single-verb structure (dominant Bloom verb)**

Each ILO should be built around a single, clearly defined action verb that corresponds to a specific level of Bloom’s taxonomy. This “dominant verb” determines the cognitive level of the outcome and ensures that the expected learner performance is precise and unambiguous. When multiple actions are present in a single statement, it becomes unclear which cognitive level is targeted and how the outcome should be assessed. Therefore, if an outcome implies several competencies, it should be split into multiple ILOs, each with its own clearly defined verb. This approach improves both the interpretability of outcomes and their alignment with teaching and assessment methods.

**Recommended syntax**

To promote uniformity and readability, all ILOs should follow a consistent, learner-centred sentence structure, beginning with:

*"By the end of the module, the learner will be able to…"*

This formulation ensures that outcomes are explicitly framed from the learner's perspective and clearly describe the expected achievement. It also facilitates consistency across courses, making ILOs easier to compare, evaluate and integrate into a broader curriculum framework. Where appropriate, the statement may also include the object of the action (what is being performed) and, optionally, the context or condition under which the performance is expected.

**Avoidance of compound outcomes**

ILOs should represent a single, measurable learning achievement. Compound outcomes—those that combine multiple verbs or describe several objectives within one sentence—should be avoided, as they complicate both classification and assessment. Such outcomes often require multiple evaluation methods but do not clearly indicate how success should be measured. Instead, complex competencies should be decomposed into a set of simpler, focused ILOs, each addressing one specific action. This not only improves assessability but also enhances transparency for both learners and instructors, as each outcome can be directly linked to a corresponding learning activity and assessment task.

By applying these standardized formulation rules, WP2-A2 ensures that all defined ILOs are precise, measurable and aligned with Bloom's taxonomy. This creates a solid foundation for coherent curriculum design, transparent assessment and effective comparison across partner institutions.

## 2.4 Target Bloom level progression

To ensure coherence and appropriate cognitive development across the AI curriculum, WP2-A2 defines a target progression of Intended Learning Outcomes (ILOs) based on Bloom's taxonomy. This progression reflects the need to move beyond basic knowledge acquisition toward higher-order competencies that are essential for modern AI practice.

**From Apply → Analyse → Evaluate → Create**

The defined ILOs are designed to follow a structured progression across Bloom's higher cognitive levels, starting from Apply and advancing through Analyse and Evaluate to Create. While lower levels such as Remember and Understand remain relevant, they are not the primary focus of the MOOCs, as WP2-A1 has shown that these are already well covered in existing curricula. Instead, the emphasis is placed on enabling learners to apply AI methods in practical contexts, analyse data and model behaviour, critically evaluate solutions, and ultimately design and develop new AI systems. This progression ensures that learners develop not only technical proficiency but also critical thinking and problem-solving skills.

**Differentiation by course/module type**

The target Bloom levels are further adapted depending on the type and purpose of each course or module. Introductory or foundational modules are expected to focus primarily on Apply and Analyse, ensuring that learners can implement and interpret AI methods. More advanced or specialised modules should increasingly target Evaluate and Create, supporting the development of independent problem-solving, system design and innovation. Application-oriented modules, particularly those focused on engineering or industrial contexts, should emphasise Apply and Evaluate, while project-based or capstone modules are expected to reach the Create level.

By defining this progression, WP2-A2 ensures that the resulting ILOs support a balanced and purposeful development of competencies, aligned with both academic expectations and real-world AI practice.

# 3. Key findings from WP2-A1 relevant for ILO definition

This section summarises the key findings of WP2-A1 that are most relevant for defining the desired Intended Learning Outcomes (ILOs) in WP2-A2. It provides a concise overview of the current state of AI education across partner institutions, highlighting both strengths and identified gaps. These insights serve as the foundation for shaping a targeted and forward-looking set of ILOs that complement existing curricula while addressing missing competencies.

## 3.1 Strengths across partner institutions

The WP2-A1 analysis shows that partner institutions share several strong foundations in AI and machine learning education.

- A key strength is the **well-established classical machine learning foundation**, with widespread coverage of supervised learning methods and core algorithms. This ensures that students develop a solid theoretical and methodological base.
- In addition, **data preparation and model evaluation** skills are consistently included across curricula. Topics such as data cleaning, feature engineering, and validation techniques are commonly taught, supporting good experimental practice.
- Finally, there is broad exposure to **basic Python and data-related tools**, particularly libraries such as NumPy, pandas and scikit-learn. This provides students with essential practical skills for working with data and implementing machine learning solutions.

Together, these strengths form a solid baseline on which more advanced and application-oriented competencies can be built.

## 3.2 Identified gaps in current curricula

Despite strong foundations, the WP2-A1 analysis highlights several important gaps in current AI curricula across partner institutions.

- One major gap is the **limited coverage of advanced learning paradigms**, such as transfer learning, self-/semi-supervised learning and online learning, which are increasingly important in modern AI applications.

- There is also a clear lack of focus on **AI deployment and model lifecycle management** practices, including model packaging, versioning, monitoring and reproducibility, which are essential for transitioning from prototype models to real-world systems.
- In terms of application, **industrial and domain-specific use cases** such as predictive maintenance, digital twins and quality control are largely underrepresented, limiting students' exposure to practical AI implementations.
- Another critical gap is the inconsistent inclusion of **responsible AI topics**, including ethics, fairness, privacy and regulatory compliance. These aspects are essential for aligning AI education with emerging societal and legal expectations.
- Finally, **explainability and robustness** are insufficiently addressed, despite their importance for trustworthy and reliable AI systems, particularly in safety-critical or regulated domains.

Addressing these gaps is a key objective of WP2-A2 and directly informs the definition of the desired ILOs.

## 3.3 Issues in current ILO design

The WP2-A1 analysis also revealed several challenges related to how Intended Learning Outcomes (ILOs) are currently formulated across partner institutions. While most courses include ILOs, their quality, structure and clarity vary significantly, which limits their effectiveness for teaching, assessment and comparison.

- A key issue is the presence of **heterogeneous formats and structures**, with ILOs expressed in different styles, lengths and levels of detail. Some are clearly defined and concise, while others appear as long, unstructured sentences or lists. This lack of standardisation makes it difficult to compare outcomes across courses and institutions or to align them within a unified curriculum framework.
- There is also an **overuse of vague verbs**, such as "understand," "be familiar with," or "know," which do not clearly describe observable learner performance. Such formulations make it unclear what students are expected to demonstrate and complicate the design of appropriate assessment methods.
- Another common problem is the presence of **compound and non-assessable outcomes**, where multiple actions or competencies are combined within a single statement. These compound ILOs often span several cognitive levels and require

different types of assessment, making them difficult to classify and evaluate consistently.

- Finally, many ILOs show a **lack of alignment with Bloom's taxonomy**, either by not reflecting clearly defined cognitive levels or by mixing multiple levels within one outcome. This reduces the ability to design a structured progression of learning and to ensure alignment between learning objectives, teaching activities and assessment.

Together, these issues highlight the need for a more systematic and standardised approach to ILO definition, which is addressed in WP2-A2 through clearly defined formulation rules and alignment principles.

# 4. Competence framework for AI education

To support the systematic definition and organisation of Intended Learning Outcomes (ILOs), WP2-A2 introduces a concise competence framework for AI education. This framework provides a structured way to group and interpret ILOs, ensuring alignment with both the findings of WP2-A1 and the broader objectives of the TAI project. It follows the widely adopted distinction between **knowledge, skills and competences**, complemented by a dedicated dimension for **responsible AI**, which reflects the increasing importance of ethical and societal considerations in the field.

The framework serves two main purposes. First, it ensures that the defined ILOs are balanced and cover all essential aspects of AI education, rather than focusing solely on technical knowledge. Second, it supports consistency across partner institutions by providing a common reference for categorising and comparing learning outcomes. This is particularly important given the diversity of programmes and disciplines represented in the consortium.

## 4.1 Knowledge domains

The knowledge domain encompasses the theoretical foundations and conceptual understanding required in AI and machine learning. Based on the WP2-A1 analysis, this includes a strong grounding in core **AI/ML paradigms**, particularly supervised learning, as well as increasing exposure to more advanced approaches. It also covers **algorithms and methods**, including their mathematical principles and assumptions, and **evaluation and validation techniques**, which are essential for assessing model performance and reliability. Strengthening this domain also involves extending coverage toward modern paradigms that are currently underrepresented.

## 4.2 Skills domains

The skills domain focuses on the practical abilities required to implement and apply AI methods in real-world contexts. This includes **programming and tool usage**, particularly in Python and widely used ML frameworks, which are already well represented across partner institutions. It further encompasses **model development and experimentation**, including data preprocessing, training, tuning and validation. Importantly, in response to identified gaps, this domain also includes **deployment and reproducibility skills**, such as packaging models, managing experiments and ensuring consistent results across environments, which are essential for modern AI workflows.

## 4.3 Competence domains

The competence domain refers to the ability to apply knowledge and skills in complex, real-world situations. This includes **problem-solving in AI contexts**, where learners must translate real-world challenges into appropriate AI tasks. It also involves **system design and integration**, combining multiple methods, tools and data sources into functional solutions. Additionally, **critical evaluation of AI solutions** is a key competence, enabling learners to assess model performance, limitations and suitability for specific applications. These competences are particularly important for bridging the gap between academic learning and industrial practice.

## 4.4 Responsible AI competencies

Given the increasing societal impact of AI systems, the framework explicitly includes a dimension dedicated to responsible AI. This encompasses **ethical considerations and fairness**, ensuring that AI systems do not introduce or amplify bias; **privacy and legal compliance**, particularly in relation to data protection and emerging regulatory frameworks; and **sustainability and societal impact**, including the broader consequences of deploying AI technologies. WP2-A1 findings indicate that these topics are currently inconsistently addressed across partner curricula, making their explicit inclusion in the competence framework essential.

Overall, this competence framework provides a clear and balanced structure for defining the desired ILOs. It ensures that the outcomes developed in WP2-A2 address not only technical knowledge, but also practical skills, real-world competences and responsible AI considerations, thereby supporting a comprehensive and future-oriented approach to AI education.

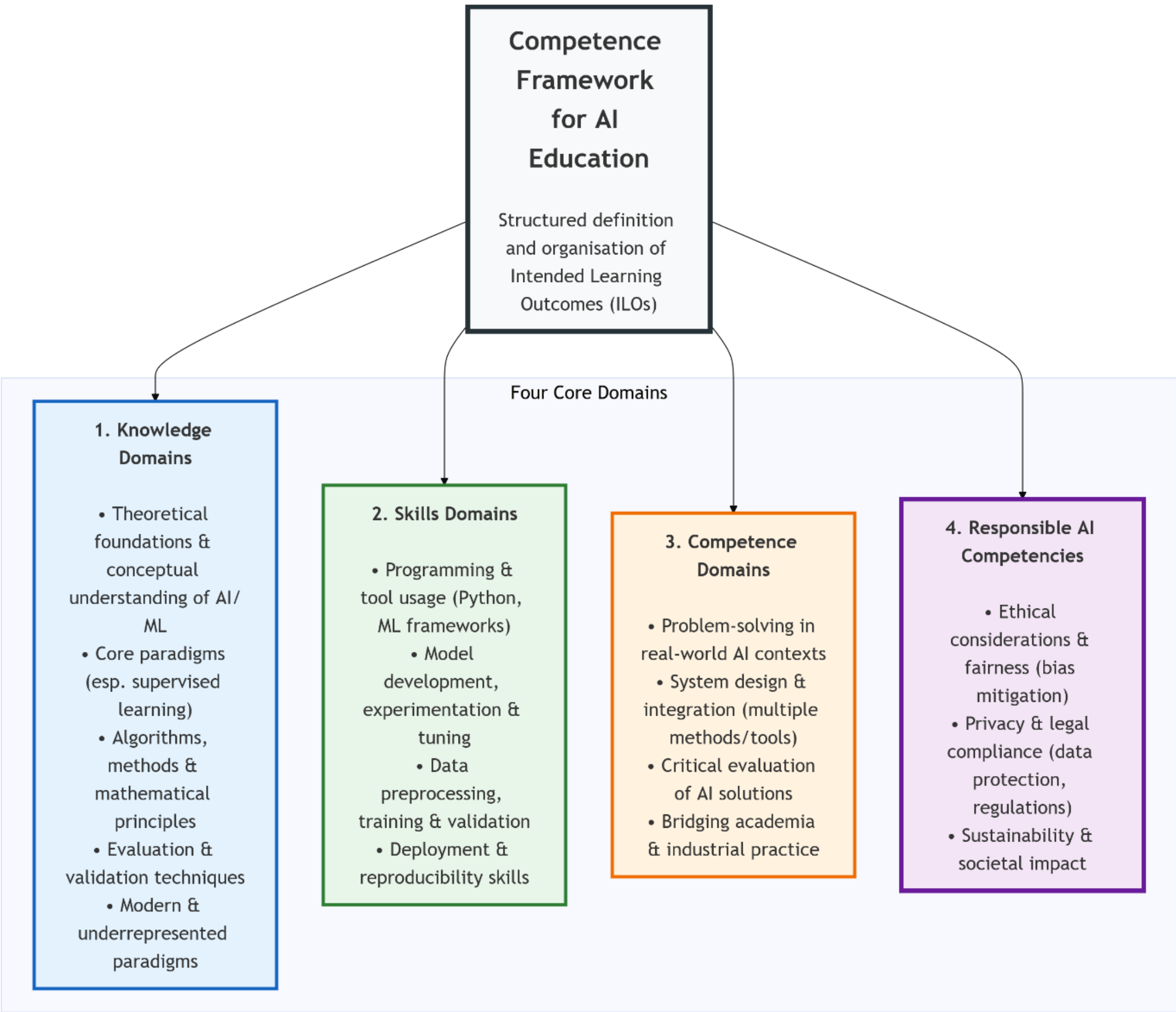


***Figure 1: Competence Framework for AI Education***

# 5. Definition of desired ILO categories

Based on the findings of WP2-A1 and the competence framework introduced in the previous section, the desired Intended Learning Outcomes (ILOs) are organised into a set of thematic categories. These categories reflect both the current strengths of partner institutions and the key gaps identified in existing curricula. Their purpose is to ensure that the final set of ILOs is comprehensive, balanced and aligned with the evolving demands of AI education.

The categorisation also supports consistency across partner institutions by providing a clear structure for grouping outcomes. It ensures that all relevant dimensions—ranging from theoretical foundations to practical implementation, system-level competences and societal considerations—are systematically addressed. Each category corresponds to a distinct area of competence and contributes to the overall goal of developing well-rounded AI graduates.

## 5.1 Core AI and machine learning ILOs

This category covers the foundational knowledge and skills that form the basis of all AI and machine learning education. As identified in WP2-A1, this is an area where partner institutions already demonstrate strong coverage, and it therefore serves as the starting point for further development.

ILOs in this category focus on understanding and applying core AI/ML concepts, including supervised and unsupervised learning, basic algorithms, and data-driven modeling approaches. They also include competencies related to data preprocessing, feature engineering, and model evaluation using appropriate metrics. The emphasis is on ensuring that learners can correctly select and apply standard methods to well-defined problems, interpret results and understand their limitations.

While this category does not represent a primary gap, it remains essential to ensure coherence and continuity in the curriculum. The goal is not to duplicate existing content, but to reinforce and modernise the core where necessary, ensuring that it supports progression toward more advanced competencies.

## 5.2 Advanced AI paradigms

This category directly addresses one of the most significant gaps identified in WP2-A1: the limited presence of modern AI paradigms in current curricula. It focuses on expanding learner competencies beyond classical approaches toward more contemporary and scalable methods.

ILOs in this category include the ability to understand, apply and evaluate approaches such as deep learning, transfer learning, self-supervised and semi-supervised learning, and reinforcement learning. Where appropriate, learners should also be able to compare these paradigms with traditional methods and identify suitable use cases.

The emphasis is not only on theoretical understanding, but also on practical application and critical evaluation. Learners should be able to select appropriate paradigms based on problem characteristics, data availability and computational constraints. This category ensures that graduates are prepared to engage with state-of-the-art AI methods and adapt to ongoing developments in the field.

## 5.3 Model development, evaluation, and explainability

This category focuses on the end-to-end process of building, analysing and interpreting AI models. While aspects of model development and evaluation are already present in current curricula, WP2-A1 highlights the need for deeper and more systematic treatment, particularly in the area of explainability.

ILOs in this category include competencies related to designing and training models, performing systematic experimentation, tuning hyperparameters and validating performance using appropriate methodologies. In addition, strong emphasis is placed on **model evaluation**, including the use of robust validation strategies, comparison of models and interpretation of results.

A key extension within this category is **explainability**, where learners are expected to understand and apply techniques for interpreting model behaviour, identifying biases and assessing reliability. This includes both global and local explanation methods, as well as critical reflection on model transparency and trustworthiness.

Overall, this category ensures that learners move beyond simple model usage toward a deeper understanding of how models behave, how they should be evaluated and how their outputs can be interpreted in real-world contexts.

## 5.4 AI deployment, maintenance, and reproducibility

This category addresses one of the most prominent gaps identified in WP2-A1: the lack of coverage of deployment and production-oriented AI workflows. While many courses focus on model development in isolated environments (e.g., notebooks), there is limited emphasis on how models are integrated into real systems.

ILOs in this category include competencies related to deploying models as services, managing model lifecycle, and ensuring reproducibility of results. This involves knowledge and skills in areas such as containerisation (e.g., Docker), experiment tracking (e.g., MLflow), version control, and monitoring model performance in production environments.

Learners should be able to transition from experimental prototypes to deployable solutions, understanding the challenges associated with scalability, reliability and maintainability. Reproducibility is emphasised as a core principle, ensuring that experiments can be replicated and validated.

By including this category, WP2-A2 ensures that AI education reflects real-world practices and prepares students for industry requirements, where deployment and maintenance are critical components of AI systems.

## 5.5 Application-oriented ILOs (engineering and industry)

This category focuses on the application of AI methods in real-world domains, particularly in engineering and industrial contexts. WP2-A1 identified that application-oriented content is currently limited and concentrated in specific niches, highlighting the need for broader and more systematic inclusion.

ILOs in this category aim to ensure that learners can apply AI techniques to solve domain-specific problems, such as predictive maintenance, quality control, digital twins, or optimisation of industrial processes. This includes the ability to define problems, select appropriate methods, integrate data from different sources and evaluate solutions in context.

An important aspect of this category is the development of **practical competences**, where learners work on realistic scenarios, case studies or project-based tasks. The focus is on bridging the gap between theoretical knowledge and practical implementation, ensuring that learners can operate effectively in interdisciplinary environments.

This category supports the overall objective of making AI education more relevant to industry needs and enhancing the employability of graduates.

## 5.6 Responsible AI and societal impact

This category reflects the growing importance of ethical, legal and societal considerations in AI. WP2-A1 findings indicate that these topics are currently inconsistently addressed across partner institutions, making their inclusion a key priority.

ILOs in this category include the ability to evaluate AI systems in terms of **fairness**, **bias**, **transparency** and **accountability**, as well as to understand issues related to **data privacy and legal compliance**, particularly within the European regulatory context. Learners should also be able to assess the broader **societal and environmental impact** of AI systems, including sustainability considerations.

Importantly, responsible AI is not treated as an isolated topic, but as a cross-cutting dimension that should be integrated across all categories. Learners should be encouraged to consider ethical implications alongside technical performance throughout the model development lifecycle.

By explicitly defining this category, WP2-A2 ensures that AI education within the project aligns with contemporary expectations and promotes the development of responsible, accountable and socially aware AI practitioners.

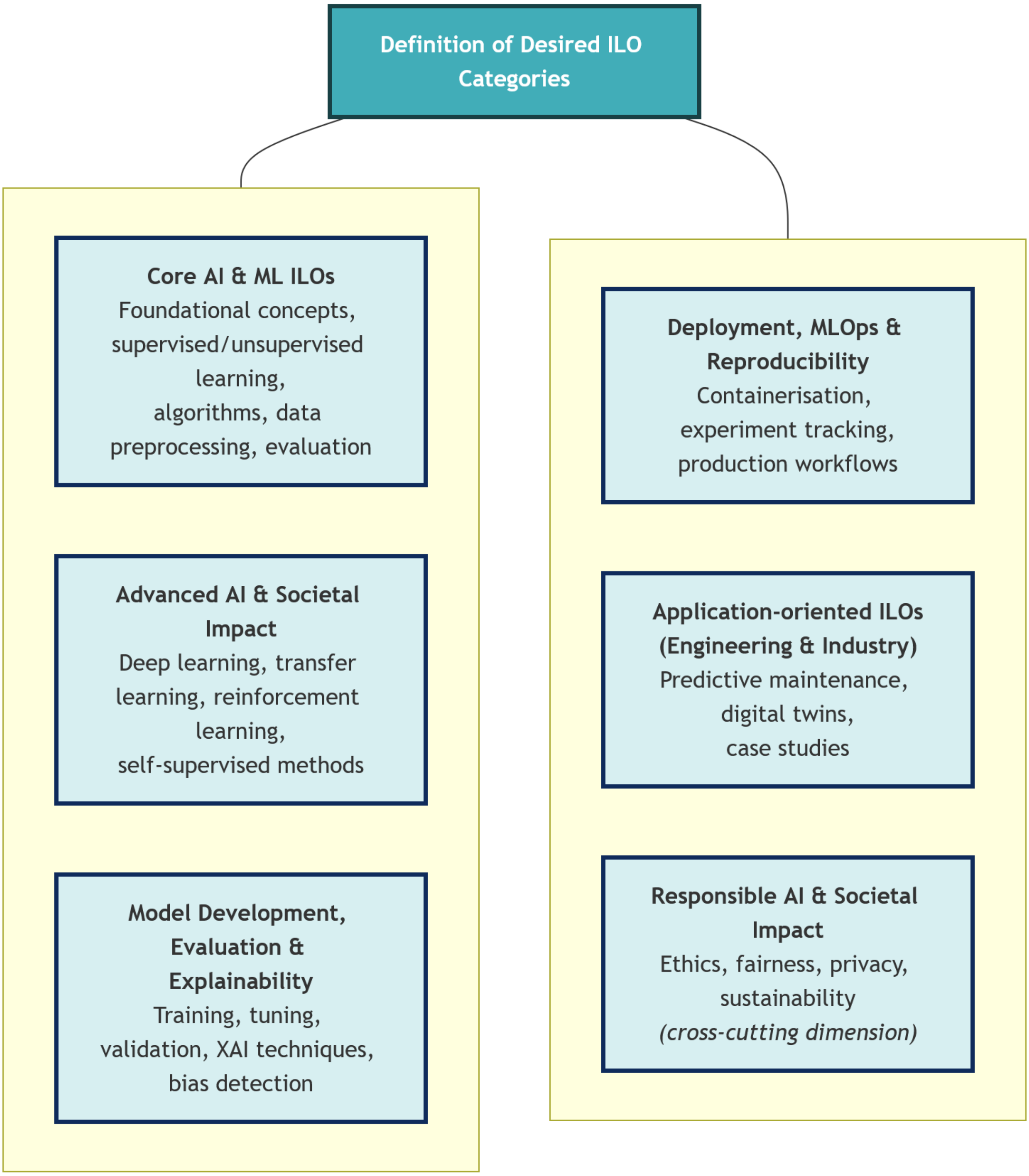


***Figure 2: Desired ILO categories with key emphasis***

# 6. Partner contributions to desired ILOs

The definition of desired Intended Learning Outcomes (ILOs) in WP2-A2 is based on a collaborative process that integrates inputs from all partner institutions. Each partner contributed existing ILOs and course descriptions, which were systematically analysed and aligned within a common framework. This section presents how these contributions were interpreted, structured and harmonised into a unified set of outcomes.

## 6.1 Overview of partner-specific priorities

The definition of desired Intended Learning Outcomes (ILOs) is based on contributions from all partner institutions (**UNILJ, UNSA, UNBG, UoM, UNIRI**) through collected syllabi and extracted ILOs.

Across the consortium, a common baseline is observed:

- strong emphasis on **supervised learning and classical ML methods**
- consistent inclusion of **data preparation and model evaluation**
- widespread use of **Python-based tools and frameworks**

At the same time, each partner exhibits specific priorities:

- **UNILJ** – balanced focus on theory, implementation, and full ML workflow
- **UNSA** – stronger orientation toward **theoretical foundations and formal methods**
- **UNBG** – emphasis on **problem formulation, system integration, and applied AI engineering**
- **UoM** – focus on **embedded AI and control-oriented applications**
- **UNIRI** – broader methodological coverage and strongest inclusion of **ethical/legal aspects** among partners

These differences form the basis for a complementary and comprehensive ILO framework.

## 6.2 Mapping partner ILOs to common framework

All partner ILOs were mapped to a shared AI/ML competency framework defined in WP2-A1, covering:

- core concepts and paradigms
- algorithms and techniques

- model development and evaluation
- tools and programming
- applications
- ethical and societal aspects

The mapping reveals the following patterns:

- **UNILJ**
    - strong alignment with:
        - data preparation, evaluation, and ML workflows
    - ILOs frequently include:
        - *apply*, *analyse*, *evaluate*
- **UNSA**
    - mapped primarily to:
        - theoretical concepts (statistics, logic, fuzzy systems)
    - ILOs dominated by:
        - *understand*, *apply*
- **UNBG**
    - strong mapping across multiple categories:
        - algorithms, system design, and applications
    - ILOs frequently include:
        - *define*, *select*, *integrate*, *evaluate*
    - notable for:
        - linking **method selection → implementation → real-world application**

- **UoM**
    - mapped to:
        - engineering applications (embedded AI, control systems)
    - ILOs emphasize:
        - *apply*, *implement*

- **UNIRI**
    - broadest mapping across:
        - ML/DL, NLP, data mining, and ethics
    - ILOs frequently include:
        - *design*, *evaluate*, *critically assess*

Overall, all partners contribute to the **core ML competencies**, while differences appear in **depth, application**

## 6.3 Identification of shared vs. unique competencies

**Shared competencies (across all partners)**

The following competencies are consistently present:

- understanding of **AI/ML fundamentals**
- ability to **apply machine learning algorithms**
- competence in **data handling and pre-processing**
- ability to **evaluate model performance**
- use of **programming tools (primarily Python)**

These form the **core ILO baseline** for the consortium.

**Partially shared competencies**

Present in several but not all institutions:

- **deep learning methods**
- **advanced model optimization techniques**
- **domain-specific applications (robotics, signal processing, etc.)**
- **use of modern ML/DL frameworks (TensorFlow, PyTorch)**

**Unique or distinguishing competencies**

- **UNBG**
  - system-level competencies:
    - problem formulation
    - method selection
    - integration of multiple AI techniques
  - strong emphasis on:
    - **end-to-end AI system design**
- **UNILJ**
  - strong focus on:
    - **complete ML pipeline (data → model → evaluation)**

- **UNSA**
  - emphasis on:
    - **formal reasoning, statistics, and logic-based approaches**
- **UoM**
  - specialization in:
    - **embedded AI and intelligent control systems**
- **UNIRI**
  - strongest contribution in:
    - **ethical, legal, and societal aspects of AI**
  - broader methodological diversity (e.g., NLP, data mining)

## 6.4 Harmonization process across institutions

To define a unified set of desired ILOs, a harmonization process was applied:

1. **Extraction and normalization**
   - ILOs from all partners were collected and reformulated into a consistent structure
   - ambiguous or vague formulations were clarified
2. **Bloom taxonomy alignment**
   - ILOs were classified according to cognitive levels:
     - *understand → apply → analyse → evaluate → create*
   - preference was given to:
     - **measurable and assessable verbs**
3. **Clustering and merging**
   - similar ILOs across partners were grouped
   - redundant outcomes were merged into unified formulations
4. **Balancing contributions**
   - ensure representation of:
     - theoretical foundations (UNSA)
     - applied/system competencies (**UNBG**)
     - engineering applications (UoM)
     - data workflows (UNILJ)
     - responsible AI (UNIRI)
5. **Gap addressing**
   - additional ILOs introduced where coverage was weak:
     - advanced paradigms (e.g., transfer learning)

- AI model deployment and model lifecycle management
- ethical and regulatory aspects

## 6.5 Conclusion

By integrating all partners which significantly strengthens the **system-level and application-oriented dimension**—the final ILO framework achieves:

- **consistency across institutions**
- **coverage of the full AI/ML lifecycle**
- **balanced cognitive levels (Bloom taxonomy)**
- **alignment with academic and industry needs**

This harmonized approach ensures that the resulting ILOs are both **comprehensive and transferable across different educational contexts**.

# 7. Consolidated list of desired ILOs

This section presents the principal outcome of WP2-A2: the consolidated set of desired Intended Learning Outcomes (ILOs) for the AI teaching materials to be developed within the TAI project. The ILOs were derived through a systematic process combining the findings of WP2-A1, partner-specific contributions, the competence framework introduced in this report, and the harmonization methodology described in the previous sections. The resulting framework provides a common educational reference for all partner institutions while remaining sufficiently flexible to accommodate different disciplinary contexts, study programmes and teaching formats.

The consolidated ILO set is intended to support the development of high-quality, outcome-based AI educational materials across the consortium. It preserves the strong foundations already present in existing curricula while explicitly addressing the curricular gaps identified in WP2-A1, particularly in the areas of advanced AI paradigms, explainability and robustness, deployment and reproducibility, application-oriented problem solving, and responsible AI. As such, the consolidated ILO framework represents the common educational foundation upon which the subsequent project activities, including the definition of the final project ILOs and the development of the TAI MOOCs, will be built.

## 7.1 Final desired ILO set

The final unified ILO set is organised into the six thematic categories defined in Section 5. All ILOs follow a standardised formulation based on the principles established earlier in this report:

- learner-centred wording
- one dominant Bloom verb per outcome
- one measurable achievement per statement
- concise and assessable phrasing

To maintain consistency, all ILOs follow the same format:

**“By the end of the module, the learner will be able to…”**

The consolidated set below is intended as a **common reference framework** for the project. Individual MOOCs or modules may use a subset of these ILOs, but the overall teaching portfolio should collectively cover the full set.

**Table 1. Consolidated desired ILOs**

| Code | Category | Consolidated desired ILO |
|---|---|---|
| **ILO-1** | Core AI and Machine Learning | By the end of the module, the learner will be able to **explain** the main paradigms, concepts and algorithm families of artificial intelligence and machine learning. |
| **ILO-2** | Core AI and Machine Learning | By the end of the module, the learner will be able to **apply** standard supervised and unsupervised learning methods to well-defined data analysis problems. |
| **ILO-3** | Core AI and Machine Learning | By the end of the module, the learner will be able to **compare** alternative model families, assumptions and performance criteria for a given AI task. |
| **ILO-4** | Advanced and Emerging AI Paradigms | By the end of the module, the learner will be able to **explain** the principles of advanced AI paradigms, including deep learning, transfer learning, self-/semi-supervised learning and reinforcement learning. |
| **ILO-5** | Advanced and Emerging AI Paradigms | By the end of the module, the learner will be able to **evaluate** the suitability of different modern learning paradigms for problems with limited labels, sequential data, interaction or domain adaptation requirements. |
| **ILO-6** | Advanced and Emerging AI Paradigms | By the end of the module, the learner will be able to **apply** an advanced AI method to solve a domain-relevant problem. |
| **ILO-7** | Model Development, Evaluation, and Explainability | By the end of the module, the learner will be able to **prepare** data for AI modelling through cleaning, transformation, feature engineering and appropriate data partitioning. |
| **ILO-8** | Model Development, Evaluation, and Explainability | By the end of the module, the learner will be able to **evaluate** AI models using suitable metrics, validation strategies and error-analysis procedures. |

| Code | Category | Consolidated desired ILO |
|---|---|---|
| **ILO-9** | Model Development, Evaluation, and Explainability | By the end of the module, the learner will be able to **analyse** model behaviour using explainability and interpretability techniques. |
| **ILO-10** | Model Development, Evaluation, and Explainability | By the end of the module, the learner will be able to **improve** model robustness through tuning, regularisation and appropriate handling of data imbalance or uncertainty. |
| **ILO-11** | AI deployment, maintenance, and reproducibility | By the end of the module, the learner will be able to **package** an AI model into a reproducible workflow, application or service. |
| **ILO-12** | AI deployment, maintenance, and reproducibility | By the end of the module, the learner will be able to **reproduce** experimental results using versioned code, documented settings and managed data resources. |
| **ILO-13** | AI deployment, maintenance, and reproducibility | By the end of the module, the learner will be able to **analyse** deployed model performance and identify possible failure modes, drift or monitoring needs. |
| **ILO-14** | Application-Oriented ILOs (Engineering and Industry) | By the end of the module, the learner will be able to **formulate** an engineering or industrial problem as an AI task, including appropriate data, constraints and evaluation criteria. |
| **ILO-15** | Application-Oriented ILOs (Engineering and Industry) | By the end of the module, the learner will be able to **design** an AI-based solution for a real-world application such as predictive maintenance, quality control, digital twins or intelligent control. |
| **ILO-16** | Application-Oriented ILOs (Engineering and Industry) | By the end of the module, the learner will be able to **integrate** models, data pipelines and domain requirements into a functional prototype, workflow or case-based solution. |
| **ILO-17** | Responsible AI and Societal Impact | By the end of the module, the learner will be able to **evaluate** AI solutions with respect to fairness, privacy, transparency and relevant legal or regulatory requirements. |

| Code | Category | Consolidated desired ILO |
| --- | --- | --- |
| **ILO-18** | Responsible AI and Societal Impact | By the end of the module, the learner will be able to **assess** the societal and environmental implications of AI deployment in a given context. |

## Interpretation of the desired ILO set

The consolidated set is intentionally balanced between foundational, technical, applied and societal dimensions of AI education.

The first category preserves the consortium's existing strengths by ensuring that all learners develop a solid grasp of core concepts and are able to use standard machine learning methods. The second category expands this baseline toward modern paradigms that WP2-A1 identified as insufficiently represented in current curricula. The third category strengthens model development beyond mere implementation by requiring robust evaluation, interpretability and robustness-oriented thinking. The fourth category responds directly to the identified gap in AI deployment engineering and maintenance. The fifth category ensures that learners can translate AI knowledge into practical engineering and industrial contexts. Finally, the sixth category makes responsible AI a non-optional component of the educational framework, in line with European expectations and the consortium's stated ambitions.

Taken together, these ILOs define not only what learners should know, but also what they should be able to do, judge and create in contemporary AI contexts.

# 8. Conclusion

WP2-A2 represents the second stage of the ILO analysis process within the TAI project. Building on the evidence gathered in WP2-A1, this activity translated the identified curricular strengths, gaps and formulation issues into a structured and harmonised set of desired Intended Learning Outcomes (ILOs). The resulting consolidated ILO set reflects contributions from all partner institutions and provides a common educational reference for the subsequent finalisation of project-level ILOs.

The work completed in WP2-A2 establishes a clear connection between the analysis of current AI education and the future development of project teaching materials. It preserves the strong foundations already present across partner curricula while extending the desired outcomes toward underrepresented areas, including advanced AI paradigms, model explainability and robustness, deployment and reproducibility, industrial applications, and responsible AI. At the same time, the use of standardised formulation rules improves the clarity, measurability and comparability of the proposed outcomes.

## 8.1 Summary of key contributions

WP2-A2 makes the following key contributions to the TAI project.

**1. Development of a consolidated and standardised ILO framework**

A primary contribution of WP2-A2 is the creation of a **unified set of desired ILOs**, based on inputs from all partner institutions and grounded in empirical analysis. This framework:

- defines clear and measurable learning outcomes
- applies a consistent formulation structure
- ensures alignment with Bloom's taxonomy
- supports comparability across institutions

This directly addresses previously identified issues related to inconsistent wording, vague verbs and non-assessable outcomes.

**2. Systematic integration of partner contributions**

The work integrates diverse inputs from **UNILJ, UNSA, UNBG, UoM and UNIRI**, ensuring that the final ILO set reflects:

- shared competencies across the consortium

- complementary strengths of individual partners
- a balanced representation of theoretical, practical and applied perspectives

In particular, the inclusion of **UNBG** strengthened the framework in terms of:

- system-level thinking
- problem formulation
- integration of AI methods in real-world contexts

**3. Alignment with identified curricular gaps**

A key contribution of WP2-A2 is the explicit alignment of ILOs with the gaps identified in WP2-A1. The consolidated framework ensures improved coverage of:

- **advanced AI paradigms** (e.g., deep learning, transfer learning)
- **AI deployment and model lifecycle management practices**
- **application-oriented and industrial AI use cases**
- **responsible AI and societal impact**
- **explainability and robustness**

This ensures that the developed ILOs are not only descriptive, but also **strategically targeted toward future educational needs**.

**4. Establishment of a competence-based structure**

The introduction of a **competence framework (knowledge, skills, competences, responsible AI)** provides a clear structure for organising ILOs and interpreting their role within the curriculum. This supports:

- balanced coverage of learning dimensions
- alignment with European educational frameworks
- improved curriculum design and communication

**5. Preparation for the finalisation of project ILOs**

The consolidated desired ILO set developed in WP2-A2 provides the direct input for WP2-A3. In the next activity, these outcomes will be further reviewed, mapped, prioritised and refined into the final set of project ILOs that will guide the development of the TAI teaching materials and MOOCs.

Overall, WP2-A2 provides the transition from the analytical findings of WP2-A1 to the final project-level outcome definition in WP2-A3. Its main contribution is therefore not yet the final specification of the project ILOs, but the establishment of a coherent, evidence-based and consortium-wide set of desired ILOs from which the final project framework can be derived.

**Lead Partner**

UNIVERZA V LJUBLJANI
University of Ljubljana

**Partners**

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