A Pedagogy-Aware Model-Driven Engineering Approach for AI Literacy

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Abstract

Artificial Intelligence (AI) literacy is becoming an essential competency across disciplines and stakeholders. However, AI-related education poses important difficulties, as it combines many concerns such as technical skills, ethical/legal issues, critical thinking, etc. These difficulties, combined with the variety of learners background, push towards customizable learning support. Such needs could be better addressed through machine processable representations, as those enable distribution, reuse, and automation mechanisms both from Model-Driven Engineering (MDE) and Generative AI techniques.

This paper proposes a framework powered by MDE methodologies to support the conceptualization of the AI literacy domain in terms of competencies and learning scenarios. The conceptualization is realized by means of corresponding metamodels in close collaboration with pedagogy domain experts. The expressiveness of the metamodels is demonstrated in a proof-of-concept developed for AI literacy teaching.

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CCS Concepts

• **Software and its engineering → Model-driven software engineering**; • **Social and professional topics → Computing literacy**; *Adult education.*

Keywords

AI Literacy, Model-Driven Engineering, Metamodeling, Competency Framework, Learning Scenarios, Non-Linear Learning Paths, Domain Conceptualization, Pedagogical Framework

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1 Introduction

Artificial Intelligence (AI) is becoming an integral part of professional practice, everyday life, and education [13]. This makes AI literacy an essential competency across different stakeholders, disciplines, and age groups. Educational institutions and trainers are therefore increasingly developing AI literacy curricula, competency frameworks, and learning materials for diverse target groups. At the same time, AI literacy education is inherently complex: it comprises technical knowledge, ethical considerations, legal aspects, critical thinking, and practical skills, while learners enter with heterogeneous backgrounds, learning objectives, and prior knowledge. Current learning paths are not tailored for these individual needs of learners. The design and adaptation of AI literacy learning scenarios would benefit from explicit and machine-processable representations of educational knowledge rather than isolated textual descriptions.

Despite the growing number of AI literacy frameworks and educational guidelines [19, 22, 23, 28, 38], existing approaches primarily define competencies or learning outcomes, but provide limited support to systematically model the pedagogical structures that connect competencies, learning activities, assessments, certifications, and learning paths. Furthermore, these approaches are typically intended for human interpretation rather than automated processing by educational technologies. Consequently, they provide little foundation for Model-Driven Engineering (MDE) or Generative AI (GenAI) techniques that aim to generate, personalize, or analyze AI literacy learning experiences. This motivates the development of a pedagogically grounded metamodel that integrates educational concepts into a unified and machine-processable representation.

Thus, we have investigated which concepts from pedagogy, certification, and educational structures are important for AI literacy education and how to use this information in educational processes.

The main contributions presented in this paper are an AI competency framework metamodel as well as a metamodel to describe learning scenarios. These can be used by MDE and GenAI approaches to, e.g., generate corresponding learning paths or monitor the learning process. A novelty of our solution is the representation of the intrinsic variability of the learning processes, which influences how the available learning paths are traversed by a user. We demonstrate our framework through a proof-of-concept case devoted to AI literacy teaching.

The paper is structured as follows: the next section introduces the background and related work, Section 3 introduces the Erasmus+ project *AIM-PRO* , the developed AI literacy competency framework, and relevant strategies for teacher technology integration for the development of AI competency. Section 4 introduces the metamodel grounded in pedagogy developed for AI literacy. Section 5 presents an explanation of the metamodel for a course in AI literacy at undergraduate level within a higher education context. Section 6 discusses our lessons learned, and the last section concludes.

2 Background and Related Works

The advent of the internet introduced the possibility of accessing learning material in various forms, such as tutorials, single lectures on specific topics, and even entire course material. Although at the beginning such access was mainly meant for archival and reference purposes, it soon disclosed the opportunity of offering support for distance learning forms. In this respect, since the middle of the 1990s the availability of open educational resources (OERs) has grown exponentially ranging from single YouTube videos and podcasts to structured Massive Open Online Courses (MOOCs) [33]. As a consequence, already at the beginning of 2000's the IEEE Learning Technology Standards Committee (LTSC) was targeting the interoperability and indexing of E Learning resources by means of metadata [16]. Implicitly, IEEE LTSC was trying to provide a very general data model to allow sharing and (re)use of educational resources.

Our investigations are at the intersection of three lines of research: the use of MDE to support instructional design, the formal modeling of competencies and curricula, and the automated generation of learning materials. In the following, we review each of those areas to position our contribution.

2.1 Model-driven approaches to instructional design

The idea of describing teaching and learning through explicit models has a long history in technology-enhanced learning. Educational modeling languages seek to capture "units of learning" in a form that supports reuse and interoperability across platforms [17]. Building on this tradition, several authors have applied MDE and meta-modeling techniques directly to the design and deployment of technology-enhanced learning systems. Laforcade et al., for example, examine how MDE and Model-Driven Architecture can support the modeling and deployment of such systems, while identifying the promises and challenges of this approach [18]. Bachir extends this vision in his PhD thesis by introducing Educational Cyber-Physical Systems [3]. Other work has applied model-driven techniques and tools to the implementation of concrete learning scenarios, such as the Planets game scenario [27]. Model-based approaches have also been used to design and re-engineer learning scenarios through context-awareness processes, allowing information gathered during enactment to inform subsequent adaptations of the learning design [30].

A recurring insight of this body of work is that a well-defined metamodel enables educators, instructional designers, and software developers to share a common description of a learning situation and to evolve it systematically. Our framework follows the same modeling philosophy while specifically targeting AI literacy and adding an explicit account of the variability involved in how learners navigate a scenario.

2.2 Modelling competencies and curricula

The second line of work formalizes *what* it is taught rather than *how* it is taught. Competency and curriculum models, often expressed as ontologies, represent competencies, learning outcomes, and their relationships so that curricula can be analyzed, queried, and verified for consistency. Several proposals organize competencies into structured representations and make their relationships explicit. For example, ontology-based curriculum analysis can be used to examine the alignment between courses, competencies, and program requirements [24]. Domain ontologies have also been proposed to map competency development in higher-education engineering programs, supporting the traceability of competencies within curricular structures [29].

Related efforts use ontologies to support competency management and connect competencies with learning resources, activities, and personalized learning pathways [15, 25]. Our competency framework shares these objectives by providing a structured and traceable catalogue of competency elements and their relationships. However, it is designed as an MDE artifact that feeds directly into learning-scenario modeling, and it represents prerequisite relations at the level of competency clusters rather than individual competencies.

2.3 Automated generation of learning material

Finally, a growing body of work uses automation and increasingly Large Language Models (LLMs) to produce learning materials and plan learning paths. Recent approaches use LLMs to generate personalized learning trajectories from information about learners' prior knowledge, goals, and preferences [26]. Other work combines language models with knowledge tracking so that recommended learning paths can be refined as evidence of learner mastery accumulates [21]. LLMs have also been used to personalize educational content according to student backgrounds, contexts, and interests [20].

A second, teacher-facing use case has developed in parallel. Rather than generating a trajectory for an individual learner, educators supply one or a few examples, such as an exercise, a worked solution, or a sample lesson plan, and ask an LLM to produce further artifacts of the same kind. Sarsa et al. prime a model with a single seeded exercise, comprising a problem statement, a sample solution, and its tests, and obtain new exercises of the same shape; most are judged sensible and novel, although few are directly usable without teacher adjustment [31]. Notably, the content of the generated exercises is steered by supplying free-text keywords, both technical and contextual, alongside the seed. The appeal of the approach is that it requires no formal specification as the examples and the keywords act as the specification.

This is also its main limitation. What is supposed to make the generated artifacts comparable, namely the competency they target, the proficiency level they assume, the pedagogical strategy they enact, and the constraints of the setting they belong to, remains tacit in the seed or is approximated by ad-hoc keywords, and must otherwise be inferred by the model. Comparability is therefore neither guaranteed nor verifiable. In this case, two artifacts produced from the same seed may address different competencies or sit at different levels of difficulty, and nothing in the process records what they were meant to have in common.

Systematic reviews identify content generation and adaptive or personalized learning as prominent applications of LLMs in education. At the same time, they repeatedly highlight concerns related to bias, transparency, reliability, trust, and the appropriate role of human educators [32]. This body of work demonstrates the potential of automated generation, but it generally operates through prompts, learner profiles, and unstructured content rather than through an explicit model of the underlying learning design.

2.4 Positioning

The solution proposed in this work relates to all three lines of research discussed so far, and its contribution lies in what none of them combines. Educational modelling languages formalise units of learning, but the competencies those units develop remain implicit, so a scenario cannot be validated against what it is meant to teach. Competency ontologies supply exactly that missing anchor, and some induce prerequisite graphs over it, but stop short of modelling delivery. Curriculum models bridge the two at the level of programme structure, yet fix a sequence rather than admitting the many traversals that a dependency graph in fact permits. LLM-based approaches produce genuinely adaptive trajectories, but derive them from prompts and learner profiles rather than an explicit model, leaving neither the competency targeted nor the path taken inspectable. Our framework combines these concerns: a machine-processable conceptualization that anchors learning scenarios to a competency graph and represents the space of admissible paths through them, so that adaptation is expressed in the model rather than delegated to a generator.

In addition, our framework originates as a domain conceptualization that proceeds from the bottom-up from the pedagogical foundations (see Section 3.3). In particular, it expresses the variability inherent in learning scenarios: rather than assuming a single linear path, it represents a space of possible paths through a scenario and allows progression to be informed by evidence of learner interaction and achievement. This emphasis on path variability within an MDE-based competency and scenario framework for AI literacy complements the existing work reviewed above.

3 The AIM-PRO Project

AIM-PRO [1] is a three-year Erasmus+ Alliance for Innovation that equips higher education (HE) institutions, Vocational Education (VET) providers, Small and Medium Enterprises (SMEs) and professional trainers with a coherent set of tools, frameworks, and resources for AI literacy. It addresses three intertwined skill families: deep tech skills (AI literacy proper), green skills (Sustainable AI), and resilience and entrepreneurial skills (AI and EntreComp). The project is delivered by a consortium of fifteen European partners that combines expertise in MDE, AI and Natural Language Processing, Digital Twin Engineering, Gamification, Open Education, and Pedagogical Design.

The technical core of *AIM-PRO* is a *model-driven foundational framework*, the focus of this paper, established early in the project, and progressively refined throughout its lifetime. Rather than a single artifact, it is a set of interrelated metamodels developed in parallel. One metamodel captures *learning scenarios* in AI literacy and is shaped through a multi-view modeling approach, so that different stakeholders can describe the same scenario from their own viewpoint while consistency is preserved. A second metamodel formalizes *the literacy competencies* of AI, that is, the knowledge, skills, and ethical considerations that scenarios are meant to develop. A third group of models covers green computing, assessment and personalisation, so that environmental footprint, assessment criteria, and learner profiles become first-class elements of the framework.

These metamodels are not built for their own sake; they drive the rest of the ecosystem sketched in Figure 1. They structure an open database of OERs and AI-generated learning resources, a suite of digital tools for scenario modeling, syllabus generation, digital twins for education and motivational and assessment engines, and a pedagogical framework whose certification mechanism is based on Open Badges. As the figure shows, the pedagogical framework acts as the *guiding hub* at the process level: it orchestrates the foundational framework, the learning materials, and the digital twins for education, absorbs continuous feedback from HE, VET, SME and expert stakeholders, and exposes every output to external

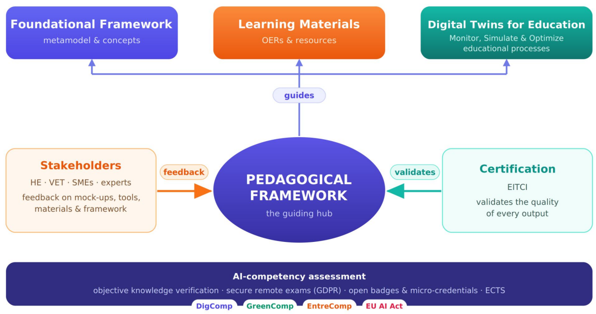

Figure 1: The *AIM-PRO* architecture. The *pedagogical framework* is the guiding hub orchestrating the foundational framework, the learning materials, and the digital twins for education. Stakeholders (HE, VET, SMEs, experts) feed back into the hub, EITCI [10] certifies every output, and all outputs are anchored to an AI-competency assessment layer aligned with DigComp, GreenComp, EntreComp, and the EU AI Act.

certification. Underpinning the whole stack, an AI-competency assessment layer, spanning objective knowledge verification, GDPR-compliant remote exams, open badges, micro-credentials and ECTS, is aligned with the DigComp, GreenComp, EntreComp , and EU AI Act reference frameworks. The stack is deployed and evaluated in real HE, VET, and SME contexts across Europe.

All these metamodels are engineered and made operational in JJodel [8, 34], a cloud-native, low-code language workbench for MDE that runs entirely in the browser, with no local installation. Within *AIM-PRO* , JJodel hosts the competency metamodel and the learning scenario language, supports the multi-view capabilities that let each stakeholder work on the viewpoint matching their expertise over a single underlying model, and serves as the platform on which models are validated, versioned, and exposed to the tools that generate learning support. Across a consortium of fifteen partners with heterogeneous backgrounds, this makes the foundational framework directly accessible to pedagogical designers and educators, not just to modeling experts.

3.1 Competency conceptualization as a pivot

If the pedagogical framework is the guiding center at the *process* level, the metamodel of AI literacy competencies is the pivotal point at the *conceptual* level. It provides a single, formally defined *domain conceptualization* of what learners are expected to know, do, and value, against which all other artifacts in Figure 1 (OERs, learning scenarios, assessment instruments, and Open Badge certifications) are annotated and validated. Since it also captures prerequisite and dependency relations, the conceptualization does not merely list competencies: it induces a *competency graph* over the domain. This shared semantic anchor keeps resources produced by different partners, in different modalities, mutually consistent and interoperable.

This pivot is precisely what enables *non-linear learning paths*. Traditional curricula encode AI literacy as a fixed linear sequence of modules; by contrast, *AIM-PRO* treats delivery as the on-demand assembly of learning support around a learner's current position in the competency space. Since every resource is indexed against the same conceptualization, and since the competency graph admits many traversals that all respect the underlying dependencies, learners with different backgrounds, such as a VET trainee, an SME professional, or an HE student, can enter at different points, follow different routes, and still converge on comparable, certifiable outcomes. The digital twins for education close the loop: by monitoring, simulating, and optimizing each learner's trajectory, they allow paths to be re-planned as learning progresses, rather than committing to a single route in advance. The generation of learning support, from syllabus fragments to scenario recommendations and assessments, is thus *based* on the domain conceptualization instead of being hard-coded into a course structure. It is the necessity of this connective, path-enabling artifact that we defend in detail in the remainder of the paper.

3.2 *AIM-PRO* Competency Framework

Any attempt to teach AI literacy needs to begin with a clear view of what AI literacy actually involves. The *AIM-PRO* Competency Framework provides this starting point. It sets out the competencies that learners are expected to develop, in a form that can be used to guide both teaching and assessment.

The framework is organised at three levels of granularity. A *competency* is what a learner is expected to know, do, or value, and the catalogue is a list of competencies. Competencies are grouped into *clusters*, which bundle them around a shared purpose and serve as the unit for assessment, and certification. Clusters are in turn grouped into *domains*, which represents thematic areas of AI literacy. The rest of this section elaborates on this structure; for now it suffices to read the catalogue as a set of competencies that can be viewed more coarsely, as clusters and domains.

3.2.1 A domain engineering approach. The framework builds on *domain engineering*, that is, the practice of identifying and organising the shared knowledge of a field into models that can be reused. In this case, AI literacy is treated as a domain whose competencies can be collected, compared, and structured. The framework was therefore not created from scratch, but developed by reviewing established AI literacy frameworks: extracting their competencies, comparing overlapping elements, consolidating recurring ideas, and adding topics that were still under-represented.

Six international AI literacy frameworks were brought together in this process: DigComp 2.2 [38], OECD/EC AILit 2025 [28], UNESCO AI CFS 2024 [23], Digital Promise [19], Long & Magerko 2020 [22], and Chiu et al. 2024 [9]. Among the topics that received limited attention in existing frameworks, and were therefore added, are sustainable or "green" AI, entrepreneurial resilience, and the engineering of AI systems and digital twins. The catalogue was also checked against relevant European policy instruments, including GreenComp [6], EntreComp [4], and the AI literacy provisions of the EU AI Act [11].

3.2.2 Construction of the catalogue. Construction proceeded in six phases and a concluding review iteration, with validation at each.

Source selection applied four criteria, namely institutional authority, publication or revision between 2020 and 2025, scope alignment

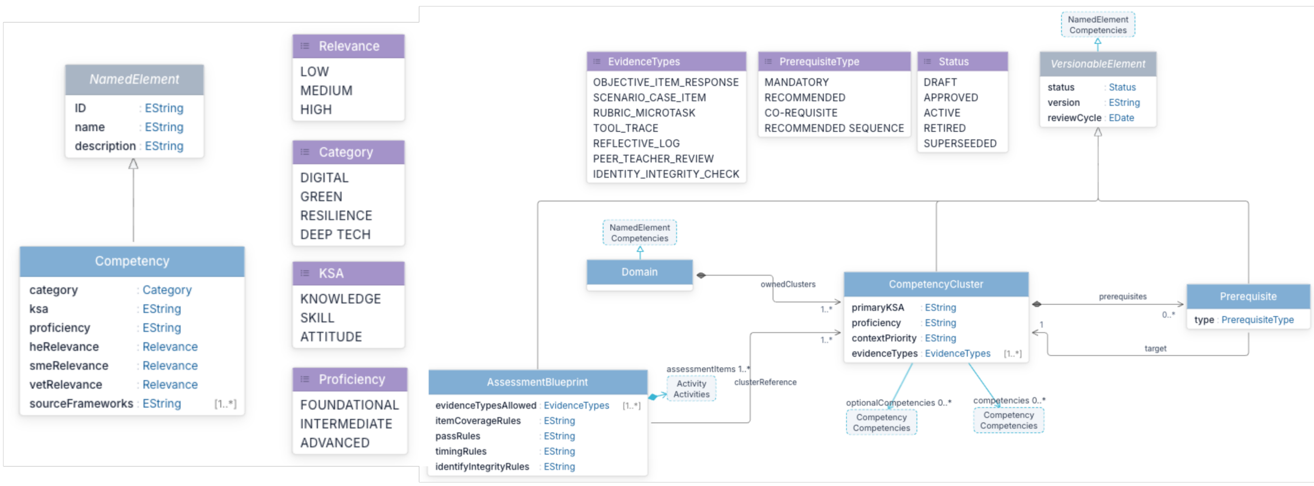

Figure 2: The *AIM-PRO* Competency Framework metamodel, as defined in JJODEL.

with the four *AIM-PRO* categories, and decomposability into KSA, yielding the six frameworks above plus three EU policy instruments used as alignment references rather than competency sources; coverage was then checked against *AIM-PRO* scope.

Extraction analysed each framework with a common template recording the competency statement, its KSA elements, proficiency indicators where available, and its source classification. Since the six frameworks differ in how finely they decompose competence, extraction took as its unit the distinct expected capability, descending below a framework's own headings where those headings were structural rather than substantive, and collapsing proficiency levels of a single capability into one item: the AI-related KSA examples of DigComp 2.2 rather than its 21 general competences, the practice-level descriptors of Digital Promise rather than its four framework registers, and the 12 competencies of UNESCO AI CFS rather than their 36 level-specific descriptors. This yielded a pool of 130 raw items, drawn as some 40 from DigComp 2.2, 25 from Digital Promise, 22 from OECD AILit, 17 from Long & Magerko, 14 from Chiu, and 12 from UNESCO AI CFS. The step was closed by a completeness review.

Cross-framework analysis compared these items semantically, treating two as the same competency when they described the same expected capability irrespective of wording, granularity or source classification. Convergence was strong in five areas: what AI is and how it works, present in all six frameworks; ethical use and critical evaluation of outputs, in five; data literacy and human-AI interaction, in four. The resulting overlap matrix and gap report were peer-reviewed within the responsible task team.

Harmonisation then merged items converging across three or more frameworks into single enriched entries, retained framework-specific items falling within *AIM-PRO* scope, and authored new competencies for the gaps, namely green computing for AI, the integration of entrepreneurial competence with AI literacy, model-driven engineering and digital twins, MLOps and lifecycle management, and adaptation to AI-driven workplace change; every entry records its provenance, with gap-fillers marked as novel, and the merged set was checked for KSA consistency.

Context mapping assigned per-setting relevance on a three-point scale from the requirements analysis, and *formalisation* fixed the abstract syntax of Figure 2, verified with partners for recall and precision. A closing iteration combined external pedagogical review with consortium-internal gap analysis, with reviewer input traced back into both catalogue and methodology. The result is the catalogue of 104 competencies.

3.2.3 *Structure of a competency.*

The result of our analysis is a catalogue of 104 competencies, organized around the four themes of the project *AIM-PRO* : Digital, Green, Resilience & Entrepreneurial and Deep Tech. Each competency is described using the same set of dimensions. First, it is linked to its main *Knowledge–Skills-Attitudes (KSA)* orientation. Second, it is assigned to a proficiency level, *Foundation, Intermediate, or Advanced*, to indicate the expected level of mastery, from the supported and careful use of AI tools to the design and supervision of AI-supported systems. Third, its relevance is rated for the three settings addressed by the project: *Higher Education, Vocational Education and Training*, and *SMEs*. This makes it possible to use a single catalogue for different audiences without duplicating competencies. For example, a competency may be essential in one setting and less central in another. Within the catalogue, 17 competencies are identified as highly relevant in all three settings and are therefore expected to be included in all curricula.

The 17 cross-cutting competencies tend to concern the responsible and ethical use of AI, which is relevant regardless of setting. Because they are essential for a Higher Education student, a VET trainee, and an SME professional alike, they form the shared backbone expected in every curriculum, while the remaining, setting-specific competencies allow each program to be tailored to its audience.

Example. The four themes populate the catalogue as follows. Under *Digital*, competencies range from critically evaluating AI-generated content to interacting with generative models through effective prompting and verifying their outputs. The *Green* theme contributes competencies such as estimating the environmental footprint of training and inference and selecting more energy-efficient models and workflows. Under *Resilience & Entrepreneurial*, the catalogue includes identifying AI-driven opportunities for value creation and adapting professional practice to AI-induced change, in line with EntreComp. The *Deep Tech* theme covers the more technical competencies, from understanding the fundamentals of a machine learning pipeline at foundation level to designing and supervising AI-supported systems at advanced level. Cutting across the four, representative examples of the 17 competencies relevant in all three settings include recognising bias and fairness issues in AI systems, understanding data protection and transparency obligations under the EU AI Act, and reflecting on the societal and professional implications of delegating decisions to AI.

3.2.4 From competencies to clusters and domains. The catalogue, however, should not be understood simply as a list. Its value also lies in the structure sketched above, which connects individual elements to broader learning goals and is formalised in the metamodel of Figure 2. Clusters are versioned units that carry a teaching goal, and they are especially useful when competencies from different themes have to be combined around a common purpose. The cluster is the unit of assessment, certification and prerequisite management. Domains are simply thematic groupings of clusters, which are useful for communicating the overall structure of the catalogue and for coverage analysis, but they do not carry any operational semantics. *Assessment blueprints* are also defined, and they specify how to assess clusters, including activities and criteria. The blueprint is the unit of assessment design for certification, and it is linked to the cluster(s) it assesses.

In this way, the movement from competencies and then to clusters links the *what* of AI literacy with the *how* of teaching it, which is developed through the learning scenarios discussed in the rest of the paper.

Example. As an example, consider the *Responsible Generative AI in Professional Practice* cluster. It combines competencies drawn from different themes around a shared purpose: from the *Digital* theme, “interact with generative models through effective prompting” and “critically evaluate and verify AI-generated content”; from *Resilience & Entrepreneurial*, “adapt professional workflows to the responsible adoption of AI”; and, from the cross-cutting responsible-use competencies, “recognize bias and comply with transparency obligations under the EU AI Act”. Each of these competencies is, in turn, decomposed into concepts: the prompting competency, for instance, unfolds into concepts such as prompt structure and context, iterative refinement, and awareness of hallucination and its verification. At the cluster level, these elements are assembled into a single, versioned unit that a curriculum designer can target as one coherent teaching goal, assess together, and certify with a dedicated Open Badge. This illustrates how a cluster bundles competencies that individually belong to separate themes but jointly serve a recognizable professional capability.

3.3 The Intelligent Synthesis of Qualitative Data model - iSQD

Preparing educators to teach effectively with digital technologies and increasingly with AI requires coordinated, evidence-based strategies rather than isolated training interventions [2]. Developing AI competencies requires more than technical skills. It requires a combination of hands-on experience, critical reflection, ethical awareness, and adaptability to fast-changing technologies [12]. Because learners differ in, e.g., their prior experience, attitudes, and self-efficacy toward technology, no single training approach fits all [5]. In this sense, training must be sensitive to individual learner profiles [cf. 14], as well as to broader equity concerns, such as disparities in digital competence [35]. These considerations motivate the use of a validated evidence-based framework capable of organizing the diverse strategies identified in the literature into a coherent structure.

To address this need, we developed the Intelligent-SQD (iSQD) model [39], an AI-specific extension of the Synthesis of Qualitative Data (SQD) model [37] and its updated version SQD2 [36]. Following PRISMA guidelines, a systematic review and meta-aggregation of 29 qualitative studies published between 2015 and 2025 used the six dimensions of SQD2 as an analytical framework,resulting in 32 strategies grouped into 12 categories and six synthesis statements. These synthesis comprehends: 1) familiarization through AI onboarding, AI-supported scenarios, and progressive exploration; 2) reflective practice on the potential and limitations of AI, role negotiation, and evaluation of AI-generated outputs; 3) collaborative design of technology-rich learning materials, co-creation with AI, AI-informed pedagogical adaptation, and iterative prompting; 4) a cycle of authentic experiences followed by feedback, addressing responsible use of AI and the emotional enrichment of AI-generated content; 5) the affective dimension (emotions, attitudes, and self-efficacy); and 6) institutional vision reinforced by institutional AI guidelines. Starting from the evidence of SQD2, the iSQD model provides an evidence-based, AI-specific pedagogical foundation that we use to ground the metamodel of learning scenarios in this paper.

4 A Pedagogically Grounded Metamodel for AI Literacy Learning Scenarios

We present the formal domain conceptualization designed to structure, manage and evaluate AI literacy learning scenarios in the *AIM-PRO* project. It takes the form of the metamodel shown in Figure 3, grounded in the iSQD pedagogical framework and in the requirements of *AIM-PRO* . The metamodel answers the need for flexible and standardized representations of pedagogical contexts, learner profiles, competency targets, and instructional strategies, allowing for precise modeling of diverse educational environments between stakeholders and learning contexts.

Structural Architecture and Core Metaclasses. The architecture is anchored by the `Scenario` metaclass, which serves as the root entity. The `learningContext` attribute categorizes the educational setting into formal value domains (HE, SME, VET), ensuring contextual adaptability across institutional boundaries.

The core of the learning journey is represented by a `pathway`, composed of a sequence of `Phase` objects. To allow for complex

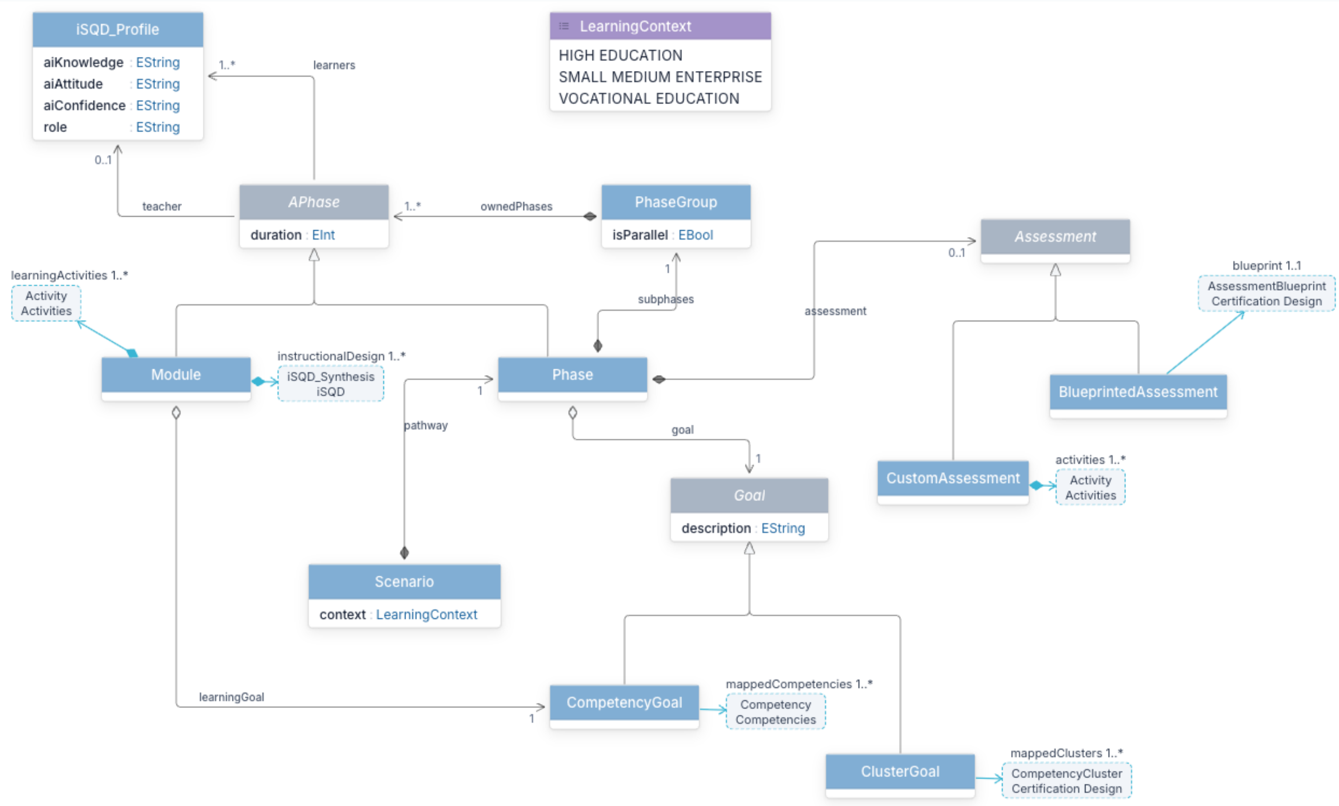

Figure 3: The proposed metamodel for AIM Pro Learning Scenarios, engineered and visualized in JJODEL.

instructional design, the metamodel employs a recursive phase structure: a `Phase` can contain sub-phases through a `PhaseGroup`, which supports both sequential and parallel instructional flows via the `isParallel` attribute. Parallel phases enable the modeling of personalized learning paths inside classes or groups, while sequential phases facilitate the representation of structured scenarios, such as those found in formal courses or training programs. The fundamental abstraction for these stages is the `APhase` (Abstract Phase), which defines the temporal dimension through a `duration` attribute and identifies the primary actors, the teacher and the learners, through `iSQD_Profile` instances. This class encapsulates the user's AI literacy traits required by the iSQD framework for designing tailored and effective pedagogical interventions. Finally, A specialized `Module` extends this abstraction, integrating instructional design synthesis, specific learning goals, and a collection of learning activities, representing the core units of the scenarios.

Competency Objectives and Framework Alignment. The metamodel adopts a goal-centric approach to learning. The `Goal` (Abstract) serves as the base for two distinct types of objectives: `CompetencyGoal` and `ClusterGoal`. Both describes the desired learning outcomes for the phase, but they differ in granularity and scope. The `CompetencyGoal` is a fine-grained objective that aligns with specific competencies defined in the *AIM-PRO* competency framework, while the `ClusterGoal` refers to `CompetencyClusters` for alignment with certification standards. Modules can be only associated with `CompetencyGoal` instances, since they are designed as self-contained units of learning for specific topics.

To assess these goals, a Phase can define an `Assessment` (Abstract), which can be either a `BlueprintedAssessment`, if it is linked to a specific `AssessmentBlueprint`, or a more generic `CustomAssessment`, which is composed of a series of `Activity` instances for formative or informal evaluation.

Instructional Sequencing and Adaptive Mechanisms. Pedagogical strategies are encapsulated through the `instructionalDesign` attribute of the `Module` metaclass, which references a list of `iSQD_Synthesis` instances. These instances define the specific pedagogical approaches defined in the iSQD framework (e.g., iterative prompting, output evaluation, reflective discussion, etc.). From these strategies, learning activities can be derived.

5 Proof-of-concept for AI literacy teaching

To demonstrate the practical applicability and semantic expressiveness of the proposed metamodel, we present a concrete model instance, which illustrates how the framework captures contextual parameters, learner profiles, competency targets, and adaptive pedagogical sequencing in a unified, machine-interpretable structure.

The listing shown in the following represents a model instance that conforms to the metamodels depicted in Figures 2 and 3. For the sake of brevity and readability, we present the model in a text-based concrete syntax.

Listing 1: Example model for an AI literacy introduction module in a HR team training context.

```
objects:
- id: D01
  title: AI Concept Understanding
- id: D05
  title: AI Output Evaluation
- id: D07
  title: AI-Augmented Decision Making
- id: D08
  title: Generative AI Literacy
- id: D10
  title: Human-AI Collaboration
- id: D11
  title: Digital Content Co-creation
- id: D16
  title: Data Privacy in AI Contexts
- id: D23
  title: AI Workflow Integration
- id: R05
  title: AI Change Management
- id: R19
  title: Stakeholder Engagement with AI
- id: R24
  title: Community of Practice Building
- id: R27
  title: Human Agency and Oversight

- id: Elena
  class: iSQD_Profile
  attributes: {role: HR Director, aiAttitude: Cautious, aiConfidence: Low}
- id: Antonio
  class: iSQD_Profile
  attributes: {role: HR team, aiAttitude: Enthusiast, aiConfidence: Medium}
- id: Anita
  class: iSQD_Profile
  attributes: {role: HR team, aiAttitude: Neutral, aiConfidence: Low}

- id: ElenaScenario
  class: Scenario
  attributes: {context: Small Medium Enterprise}
  children:
    pathway:
    - id: Phase_0
      class: Phase
      attributes: {duration: '240'}
      references: {teacher: [Elena], learners: [Antonio, Anita]}
      children:
        subphases:
        - id: PhaseGroup_0
          class: PhaseGroup
          attributes: {isParallel: false}
          children:
            ownedPhases:
            - id: Module_0
              class: Module
              attributes: {duration: '120'}
              references: {learners: [Elena]}
              children:
                instructionalDesign:
                - class: S1_Familiarization
                  children: {strategies: [SC1_BuildingAIKnowledge, SC5_ScaffoldedExploration]}
                - class: S5_AffectiveDimension
                  children: {strategies: [SC24_AttitudesAndBeliefs]}
                - class: S2_ReflectivePractice
                  children: {strategies: [SC7_RoleNegotiation, SC8_OutputEvaluation]}
                learningGoal:
                - id: CompetencyGoal_1
                  class: CompetencyGoal
                  references: {mappedCompetencies: [D01, D07, D08, D11, D05]}
            - id: Module_1
              class: Module
              attributes: {duration: '120'}
              references: {teacher: [Elena], learners: [Antonio, Anita]}
              children:
                instructionalDesign:
                - class: S4_AuthenticExperience
                  children: {strategies: [SC19_AiIntegratedClassroomTeaching]}
                - class: S3_CollaborativeDesign
                  children: {strategies: [SC15_CoCreationWithAI, SC17_IterativePrompting]}
                - class: S4_AuthenticExperience
                  children: {strategies: [SC20_EmotionalEnrichmentOfAIContent]}
                - class: S2_ReflectivePractice
                  children: {strategies: [SC8_OutputEvaluation, SC10_ReflectiveDiscussion]}
                learningGoal:
                - id: CompetencyGoal_2
                  class: CompetencyGoal
                  references: {mappedCompetencies: [D05, D10, D16, D23, R05, R19, R24, R27]}
    goal:
    - id: CompetencyGoal_0
      class: CompetencyGoal
      references: {mappedCompetencies: [D01, D05, D07, D08, D10, D11, D16, D23, R05, R19, R24, R27]}
```

The `ElenaScenario` model outlines a 240-minute AI literacy training path for an SME HR team transitioning to AI-supported candidate screening. It structures the learning into two sequential 120-minute modules: the initial module focuses on foundational AI literacy for Elena, responding to her specific learning needs and competency gaps, while the second module emphasizes collaborative team activities with Antonio and Anita. The model specifies the learning objectives, competency targets, and pedagogical strategies for each module, ensuring alignment with the overall training goals.

It should be noted that even Elena is the teacher, in the first module she is the learner. This emphasizes the metamodel's flexibility in accommodating diverse instructional designs, including scenarios where learners and teachers may interchange roles or where certain participants may be excluded from specific learning phases.

Use Cases and JJODEL Integration. The purpose of the metamodel is to provide a structured representation of the learning scenario, normally expressed as documentations or lesson plans, and it was designed to be used in conjunction with the JJODEL tool [34]. In fact, JJODEL integrates both a visual editor and a generative AI agent called JJODIE, which can create and manipulate metamodel instances simply chatting with the user. The generative AI agent can also provide suggestions for instructional design, pedagogical sequencing, and competency mapping based on the current model instance.

The generated scenario model can be exported in a machine-readable format (e.g., YAML or JSON) and acts as a blueprint for generating lesson plans, interactive learning environments, or for search relevant educational resources. The integration of JJODEL enables educators to leverage AI capabilities for scenario generation even when they lack knowledge in MDE, while maintaining control over the instructional design and pedagogical sequencing.

Figure 4 illustrates the Jjodie interface, where the user interacts with the AI agent to receive recommendations for iSQD strategies tailored to Elena's profile. The agent provides suggestions and generates the corresponding code for model manipulation in Jjodel editor.

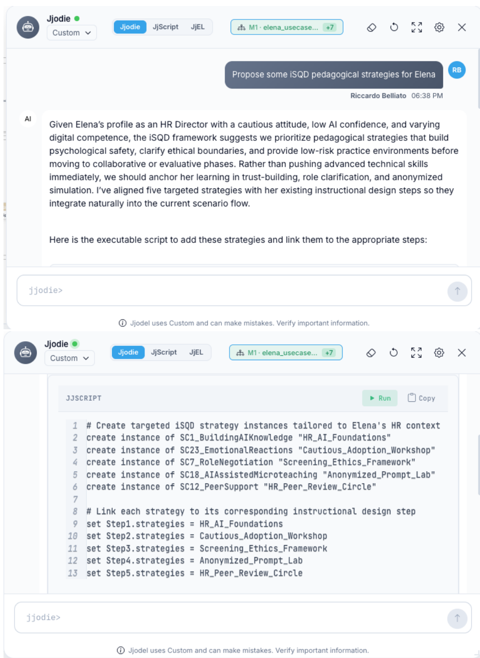

Figure 4: Jjodie interface on recommending iSQD strategies for Elena

6 Lessons learnt and Outlook

In the following, we share our experiences from domain conceptualization, how different stakeholders could use the proposed metamodel, and how digital twins can support these ideas.

6.1 On the domain conceptualization

The metamodels discussed in this paper are the result of an intense and tight collaboration between domain experts, i.e. pedagogues and language engineers. A distinguishing characteristic of our effort is that while in general language engineers tended to extract data models as common denominators of available learning resources, we proceeded in a bottom-up way: first, the pedagogues investigated and planned appropriate strategies, and then language engineers formalized those concepts in the metamodels. Thanks to this approach, it is now possible to plug-in several automation means. In particular, the metamodel does not yet include a direct mapping between iSQD strategies and specific learning activities (e.g., quizzes, lectures, discussions). However, the framework is designed to support such mapping: it could be realized by creating a specific metamodel for activities and establishing the relationship between strategies and activities; or the current models could be taken as inputs for model transformations able to extract and convert strategies towards corresponding activities; or the models could even be given as a prompt to an LLM to generate appropriate activities. In other words, the learning scenarios are kept sufficiently abstract to be applicable across different contexts, while also providing the necessary granularity for practical implementation in specific educational settings or platforms.

6.2 Stakeholders' interaction

It is expected that stakeholders will only interact with a sub-portion of the domain concepts provided by the metamodels. For example, a certification entity will define and validate the cluster of competencies necessary to achieve certain proficiency levels. Similarly, a teacher will focus on the class profiles and learning goals to design the corresponding scenarios. Therefore, we are currently investigating the design of user interfaces that will project selected parts of the domain concepts to the stakeholders. On the one hand, this will hide the underlying complexity of the foundational framework; on the other hand, the underlying metamodel can be distributed to e.g. share learning scenarios or competency clusters for certification. So, thanks to the user interfaces, it will be possible to support the separation of concerns among stakeholders.

6.3 Towards Digital Twins for Education

The pedagogical framework proposed by *AIM-PRO* includes the concept of competencies, which is inherently a dynamic aspect of education. From the teaching and certification perspectives, certain competencies might evolve over time and require refinements. Notably, a hypothetical learning scenario involving LLMs needed to evolve from the initial single-/multiple-shot queries, to prompt engineering, and eventually to the current techniques including skills and multiple agents. On the other hand, from a lifelong learning perspective, "students" are expected to progress with their competences throughout time. For example, they might complete selected math courses that would enable learning scenarios for advanced AI techniques such as vectorization. Such dynamic characteristics require running-time monitoring for the various concerns in the pedagogical framework; in this respect, the domain conceptualization proposed in this work comes in handy, as it constitutes the basis for the creation of digital twins [7] devoted to education.

7 Conclusion

The growing demand for AI literacy learning support stresses the currently available education frameworks. The variety of learners' background, needed competences, and appropriate pedagogic approaches involve a high degree of customization and automation. This paper discussed how MDE methodologies provide the solutions to precisely define the domain concepts through metamodels. metamodels can be used to formally represent competencies and learning scenarios. Moreover, the metamodels are pedagogically aware in the sense that they allow us to represent the inherent variability in the learning paths. Being machine readable, these formal representations can be used as enablers of automation mechanisms based on model transformations and GenAI techniques. The expressiveness of the proposed metamodels and the enabled automation potentials are demonstrated in the paper through a proof-of-concept scenario.

The work presented in this paper constitutes the foundational efforts to develop AI literacy for professional readiness in the context of the *AIM-PRO* project. In this respect, we also discuss the future development steps originating from the developed metamodels.

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