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DEVELOPING STUDENTS' PRACTICAL SKILLS IN ARTIFICIAL INTELLIGENCE EDUCATION THROUGH A COMPETENCY-BASED APPROACH

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Abstract: The rapid expansion of artificial intelligence (AI) across professional fields has intensified the need for educational approaches that move beyond the transmission of theoretical concepts toward demonstrable practical competence. This narrative review examines how competency-based education can be applied to the teaching of artificial intelligence in higher education, with particular attention to problem formulation, data literacy, algorithm selection, model evaluation, ethical reasoning, and collaborative project work. Drawing on research in competency-based education, experiential learning, computing education, and AI literacy, the article develops a structured instructional framework linking intended learning outcomes, authentic tasks, formative feedback, and performance-based assessment. The review argues that effective AI teaching requires the coordinated development of technical, methodological, and socio-ethical competencies. It also identifies implementation constraints, including unequal prior programming experience, limited computing resources, assessment validity, and the risk of excessive dependence on generative AI systems. The proposed framework is conceptual and requires empirical validation in specific institutional settings.

Keywords: artificial intelligence education; competency-based learning; practical skills; machine learning; project-based learning; authentic assessment; AI literacy; higher education.

Introduction

Artificial intelligence is increasingly embedded in scientific research, medicine, education, business, and public services. Universities therefore face a dual educational challenge: students need to understand the mathematical and computational foundations of AI while also learning to apply those foundations to complex, imperfect, and ethically sensitive real-world problems. A curriculum organized primarily around lectures and examinations can support conceptual knowledge, yet may provide insufficient evidence that students can independently prepare data, justify model choices, detect errors, or communicate the limitations of algorithmic predictions. This tension makes the design of practical, assessable learning outcomes a central concern in AI pedagogy [1, 2].

Competency-based education offers a useful perspective because it defines learning in terms of demonstrable abilities rather than course attendance or exposure to content alone. Competence includes the integrated application of knowledge, skills, and judgment in context. For AI instruction, this means that a student should not merely define supervised learning or describe a neural network, but should be able to formulate an appropriate task, select a defensible method, evaluate results, and explain the consequences of errors. Such an approach is compatible with constructive alignment, in which teaching activities and assessment are explicitly designed around intended learning outcomes [3].

The term "practical skills" should be interpreted broadly. Coding is essential in many AI courses, but competence also includes understanding data provenance, recognizing sampling bias, choosing

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meaningful evaluation metrics, documenting experiments, and cooperating with domain specialists. Recent AI literacy frameworks emphasize that technical performance must be accompanied by critical awareness of AI capabilities, limitations, and societal implications [4, 5]. This article considers how these dimensions can be integrated into a coherent teaching methodology.

Aim and Methods

The aim of this article is to synthesize pedagogical principles relevant to the competency-based teaching of artificial intelligence and to propose a practical framework for developing and assessing students' applied skills. The article is a narrative literature review and conceptual methodological analysis, not a report of an intervention conducted with a student sample. Its discussion draws on established literature in competency-based education, experiential and project-based learning, computing curricula, AI literacy, and responsible AI. Sources were interpreted comparatively to identify instructional elements that can be translated into higher-education AI courses. No systematic database search, meta-analysis, or original quantitative experiment was performed; accordingly, claims about effectiveness are presented cautiously.

Results and Discussion

The structure of practical competence in artificial intelligence

A competency-oriented AI curriculum should begin with a clear description of the actions students are expected to perform. The first domain is problem formulation: translating a practical question into a tractable computational task and recognizing when AI is not the appropriate solution. The second is data competence, encompassing collection, cleaning, exploratory analysis, documentation, and responsible handling of personal or sensitive information. The third domain concerns computational implementation, including programming, reproducibility, use of libraries, and debugging. The fourth is model reasoning: choosing a baseline, understanding assumptions, selecting an algorithm, and explaining its trade-offs. The fifth is evaluation and communication, including the selection of appropriate metrics, error analysis, and clear reporting of uncertainty [2, 6].

These domains are interdependent. A technically sophisticated model cannot compensate for a poorly defined question or a dataset that fails to represent the intended population. Similarly, high accuracy on a single held-out dataset does not automatically establish generalizability, fairness, or clinical or organizational usefulness. Students should therefore learn to see the AI workflow as an iterative process rather than a sequence of isolated programming exercises. Ethical reasoning, collaboration, and reflective self-evaluation should operate across the entire workflow, not appear only as supplementary lectures near the end of a course [5, 7].

Learning outcomes and curriculum alignment

The design process begins with observable outcomes stated through action verbs. For example, an introductory student may be expected to construct a baseline classifier, explain the difference between training and test data, and interpret a confusion matrix. At an intermediate level, students may compare models using cross-validation, document preprocessing decisions, and identify potential sources of data leakage. Advanced students may be required to design a reproducible experiment, assess subgroup performance, evaluate model robustness, and defend their methodological decisions in a written technical report. This progression helps instructors avoid treating every AI topic as equally appropriate for every level of preparation.

Constructive alignment requires that learning activities provide genuine opportunities to practice these outcomes and that assessment measures the same capabilities [3]. If a course outcome

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emphasizes model evaluation, an examination consisting only of definitions will be inadequate. Students should instead analyze model outputs, explain why a metric is suitable for a particular context, and identify threats to validity. Conversely, assigning a complex end-to-end project without scaffolding may overwhelm learners who lack programming or statistical foundations. Competency-based design therefore combines explicit standards with progressive support and multiple opportunities for feedback.

Experiential learning and authentic problem solving

Experiential learning theory suggests that knowledge becomes more meaningful when learners move between concrete activity, reflection, conceptual interpretation, and further experimentation [8]. AI instruction can operationalize this cycle through carefully designed laboratory tasks. Students might first train a simple predictive model on an accessible dataset, inspect errors, connect observed behavior to concepts such as overfitting, and then revise their approach. The pedagogical value lies not merely in completing the code but in explaining what changed and why. Reflection logs and short methodological commentaries can make this reasoning visible to instructors.

Authentic projects strengthen the connection between technical procedures and real-world constraints. A project might require students to predict energy consumption, categorize public-domain text, or examine a non-sensitive open dataset. The task should be sufficiently realistic to expose ambiguity, missing data, and competing objectives, yet bounded enough to remain achievable within the course. Project-based learning literature supports the use of sustained inquiry, collaboration, and tangible products, although the quality of implementation and assessment conditions substantially influences outcomes [9]. For this reason, projects should be selected for educational relevance rather than technical novelty alone.

Scaffolding technical skills across stages

An effective sequence may begin with data exploration and rule-based baselines before introducing more sophisticated machine-learning methods. Students first practice importing data, checking variable types, visualizing distributions, and identifying missing values. They then establish simple baselines, partition data appropriately, and compare alternative algorithms. Later assignments add hyperparameter tuning, interpretability, robustness checks, and documentation. This sequence makes it easier to diagnose whether difficulties arise from programming, statistics, problem understanding, or conceptual misunderstandings about model behavior.

Scaffolding also includes worked examples, partially completed notebooks, code reviews, peer explanation, and targeted feedback. Support should gradually decrease as students demonstrate independence. Differentiated entry tasks can be particularly valuable in mixed cohorts: students with limited programming experience may require additional exercises on functions, arrays, and data structures, while more advanced students can investigate optional extensions. The goal is not to lower competency standards but to provide appropriate pathways toward the same core outcomes. Instructor feedback should focus on decisions and reasoning as well as executable code.

Assessment of observable competence

Performance-based assessment is central to competency-oriented teaching. A useful evaluation rubric should consider the appropriateness of problem formulation, quality of data handling, validity of experimental design, correctness and readability of implementation, suitability of evaluation metrics, reproducibility, ethical reflection, and clarity of communication. These criteria should be shared with

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students before the project begins. Portfolios containing notebooks, concise reports, experiment logs, and revised submissions can document growth over time more effectively than a single timed test.

Assessment should combine individual and group evidence. Team projects reflect professional AI practice but may conceal unequal contributions. Individual oral defenses, brief practical checks, peer feedback, and version-control histories can help instructors determine what each student understands. Formative assessment is equally important: early feedback on data leakage, unbalanced datasets, or inappropriate metrics can prevent students from consolidating poor practices. A final grade should not depend solely on predictive accuracy, because this may reward dataset-specific optimization while overlooking conceptual errors or responsible use considerations.

Integrating responsible AI and critical literacy

Responsible AI competence requires students to examine the social and institutional conditions under which AI systems operate. Relevant topics include privacy, fairness, transparency, accountability, intellectual property, and human oversight. The UNESCO Recommendation on the Ethics of Artificial Intelligence offers a broad normative framework that can inform educational discussion, while AI literacy scholarship provides concepts for evaluating what learners should know and be able to do [5, 7]. In practice, students might compare subgroup error rates, write a dataset limitations statement, or explain why a model should not be deployed in a high-stakes setting without further validation.

Generative AI tools can assist learning by providing code explanations, debugging suggestions, and alternative examples, but their outputs can be inaccurate or misleading. Students should be taught to verify generated code, acknowledge assistance where required, protect confidential data, and demonstrate independent understanding. Instructors may permit such tools for selected tasks while designing assessments that require reasoning about unfamiliar examples or defending methodological choices. Transparent course-level rules are preferable to vague prohibitions, especially when students encounter AI assistants in their broader academic and professional environments.

Implementation challenges and institutional conditions

Competency-based AI teaching requires more than a redesigned syllabus. It depends on access to suitable computing environments, reliable datasets, instructors with pedagogical and technical preparation, and enough time for iterative feedback. Resource constraints can be mitigated by using lightweight algorithms, modest open datasets, shared computational infrastructure, and reproducible local environments. Not every meaningful AI learning outcome requires high-cost graphics processing units. In many introductory contexts, a carefully analyzed linear model can teach more about data leakage and validation than an opaque large model trained without critical reflection.

Institutions should also establish a process for reviewing curriculum relevance as AI methods evolve. This does not imply continuously replacing foundational content with new tools. Concepts such as probability, optimization, generalization, experimental design, and ethical judgment remain durable. A balanced curriculum retains these foundations while periodically updating datasets, software practices, and authentic applications. Cooperation between computing faculty and domain experts can improve the realism of projects and help students appreciate the limits of purely technical solutions.

A proposed instructional framework

The reviewed literature supports a five-stage instructional framework. The first stage defines a small set of measurable competencies appropriate to the learner level. The second maps these

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competencies to progressively demanding tasks, beginning with guided exercises and advancing toward authentic projects. The third establishes explicit assessment criteria and collects evidence through practical artifacts and individual explanation. The fourth embeds formative feedback, revision, and reflective practice throughout the course. The fifth evaluates curriculum performance through student work, learner feedback, and subsequent revisions of tasks and rubrics. These stages form a continuous improvement cycle rather than a rigid sequence.

An illustrative semester course could begin with problem formulation and data literacy, proceed through baseline modeling and evaluation, and culminate in a supervised project that includes reproducibility and responsible-AI documentation. Each module would have a demonstrable output, such as a data audit, validated baseline, error analysis, or methodological justification. This model is offered as a pedagogical synthesis rather than an experimentally proven intervention. Future studies should compare it with conventional lecture-centered instruction using transparent rubrics, baseline equivalence checks, and outcomes that measure transfer to unfamiliar problems.

Conclusion

Competency-based teaching offers a coherent foundation for developing students' practical skills in artificial intelligence. Its principal contribution is to connect what students learn with what they can demonstrate in realistic situations. Effective implementation requires explicit learning outcomes, progressive technical scaffolding, authentic tasks, formative feedback, and assessments that value reasoning, reproducibility, and responsible judgment alongside functional code. AI competence should be understood as an integrated combination of problem formulation, data handling, model development, evaluation, communication, and ethical awareness.

The proposed approach also underscores the importance of institutional support and realistic course design. Project work is valuable when learners receive sufficient guidance and when assessment captures individual understanding. Generative AI tools may enrich instruction, but they must be accompanied by verification practices and clear expectations regarding independent work. Because the present article is a narrative and conceptual review, further empirical research is needed to establish how competency-based designs influence learning outcomes across student populations and educational contexts.

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