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RETHINKING INTRODUCTORY AI EDUCATION IN THE ERA OF RAPID TECHNOLOGICAL ADVANCEMENT

Abstract. This paper explores the necessity of rethinking introductory artificial intelligence education in response to rapid technological advancement and democratized AI tools. It proposes a shift from a traditional prerequisite-driven, theory-first paradigm to an experience-driven model. Early practical interaction with modern AI tools can enhance student intuition, motivation, and practical understanding. The approach is illustrated by its implementation in an introductory AI course for first-year university students.
Keywords: Artificial intelligence education, experience-driven learning, pedagogical transformation, introductory AI courses, generative AI in education.

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ПЕРЕОСМИСЛЕННЯ ВСТУПНОЇ ОСВІТИ ЗІ ШТУЧНОГО ІНТЕЛЕКТУ В ЕПОХУ СТРІМКОГО ТЕХНОЛОГІЧНОГО ПРОГРЕСУ

Анотація. У цій роботі досліджується необхідність переосмислення вступної освіти зі штучного інтелекту у відповідь на стрімкий технологічний прогрес та демократизацію інструментів ШІ. Пропонується перехід від традиційної парадигми, орієнтованої на пререквізити та теорію, до моделі, заснованої на практичному досвіді. Рання практична взаємодія із сучасними інструментами ШІ може підвищити інтуїцію, мотивацію та практичне розуміння студентів. Підхід ілюструється його впровадженням у вступному курсі з ШІ для студентів першого курсу університету.
Ключові слова: Освіта зі штучного інтелекту, навчання на основі досвіду, педагогічна трансформація, вступні курси з ШІ, генеративний ШІ в освіті.

The rapid development of artificial intelligence (AI) has substantially changed both the technological landscape and the way people interact with intelligent systems [1]. AI technologies that previously required considerable technical expertise are now accessible through cloud platforms, no-code and low-code tools, pretrained models, and generative AI systems [2]. As a result, students increasingly encounter and use AI

technologies before receiving formal university education in artificial intelligence. This technological transformation raises an important pedagogical question: should introductory AI education continue to follow an educational paradigm developed for a substantially different technological environment? The aim of this paper is to substantiate the need to rethink introductory AI education and to outline an experience-driven approach to its design.

Traditionally, introductory education in AI and machine learning has followed a prerequisite-driven sequence in which students first acquire mathematical and programming foundations, then study theoretical and formal aspects of machine learning, and only afterwards apply this knowledge in practical tasks. Such an approach has clear advantages. It provides students with rigorous foundations and allows complex concepts to be explained systematically. Historically, it was also a natural consequence of the high technical barriers associated with AI: meaningful interaction with AI systems generally required programming skills, mathematical knowledge, specialized software, and significant computational resources.

However, many of these barriers have been substantially reduced. Beginners can now experiment with AI systems without implementing algorithms from scratch or possessing advanced mathematical knowledge. No-code and low-code platforms allow students to train and evaluate simple models visually, while cloud environments provide access to computational resources and ready-to-use development environments [3]. Generative AI has further transformed this landscape by enabling users to interact with sophisticated AI systems through natural language and by assisting with tasks such as code generation, explanation, experimentation, and problem solving. Consequently, students can gain meaningful practical experience with AI much earlier in their educational journey than was previously possible.

This change does not imply that mathematical foundations, programming, or formal machine-learning theory have become unnecessary. Rather, it suggests that their position within introductory education should be reconsidered. Instead of treating practical interaction with AI as something that can only occur after all necessary prerequisites have been mastered, practical experience can be used as an initial point of contact with the subject [4]. Simplified theoretical explanations can provide students with an accessible conceptual framework, while practical activities allow them to observe how the introduced concepts behave in real or simulated situations. Subsequent theoretical education can then formalize and refine the understanding that students have already begun to develop through experience.

Such an approach can be viewed as a transition from a predominantly theory-first paradigm toward an experience-driven paradigm [4]. Its underlying educational progression can be represented as experience → observation → intuition → conceptualization → formalization → refined intuition. The purpose is not to replace rigorous theory with experimentation, but to establish an initial intuitive understanding that makes subsequent formalization more meaningful [5]. This is particularly important for the development of professional intuition: the ability to recognize patterns, anticipate potential problems, assess the plausibility of results, and make informed decisions in situations that cannot be completely described by predefined rules. At the same time, such an approach requires careful course design so that early practical experience does not lead to superficial understanding or an illusion of competence.

An introductory AI course designed according to this principle can therefore combine simplified lectures with practical experimentation and early exposure to the modern AI ecosystem. Students may interact with no-code AI tools, experiment with existing models, observe the effects of different neural-network architectures and training parameters, and work with professional environments such as GitHub, Jupyter, Google Colab, Python, Markdown, and LaTeX. The objective of these activities is not necessarily to make first-year students proficient programmers or machine-learning engineers. Instead, they provide students with an initial understanding of what modern AI workflows, tools, models, and development practices look like.

Generative AI can also be incorporated into this approach without making it a substitute for student learning. Although the use of generative AI in education is frequently criticized because students may delegate their assignments to AI systems instead of engaging with the learning process [6], its educational value depends strongly on how activities are designed. When students are encouraged to use AI to generate alternative solutions, code implementations, hypotheses, or experimental configurations and then test, compare, and critically evaluate them, AI becomes an exploratory instrument rather than an answer-generation mechanism [7]. In this context, generative AI can broaden the range of possibilities students encounter while leaving the essential processes of experimentation, evaluation, reasoning, and decision-making to the learner.

This approach has been implemented in an introductory AI course for first-year university students with minimal prior formal knowledge of artificial intelligence, mathematics, and programming. The course combines simplified theoretical lectures with practical activities that allow students to encounter important AI phenomena directly. For example, an image-classification task based on objects available in students' surroundings allows them to experience issues related to data quality, representativeness, generalization, and model failure before these concepts are introduced formally. Similarly, interactive experiments with neural networks allow students to change architectural and training parameters and observe their effects, providing intuitive foundations for later understanding of model capacity, optimization, learning rates, and overfitting.

The expected educational benefits extend beyond familiarity with individual AI technologies. Practical exposure gives students an initial mental map of the AI ecosystem and can reduce the technical barriers that frequently hinder further independent learning. Students become familiar with tools and workflows that they are likely to encounter in subsequent courses and professional environments, while simultaneously developing an intuitive understanding of how AI systems behave and how their results should be interpreted. This experience can also increase motivation to study mathematical and theoretical foundations, as students can already recognize the practical relevance of concepts that might otherwise appear abstract or disconnected from real applications. A systematic empirical evaluation of these effects is a subject of further research.

Results of the implementation

The course was piloted in 2024 with 19 first-year students majoring in Applied Mathematics. The course lasted 16 weeks and included 16 hours of lectures and 16 hours of practical work. Data were collected through anonymous pre- and post-course

surveys (5-point Likert scale) and a conceptual understanding test administered at the beginning and at the end of the course; 16 students completed both stages.

According to the surveys, self-reported confidence in working with AI tools increased from 2.8 to 4.6, and 87.5% of students reported higher motivation to study mathematical and theoretical foundations (Table 1). Students' written reflections most often mentioned better understanding of machine learning techniques, data analysis methods, and better overall understanding of how deep learning works in general.

Table 1. Results of the pre- and post-course assessment

Indicator	Before the course	After the course	Change
Self-reported confidence in working with AI tools (1–5)	2.8	4.6	1.8
Motivation to study mathematics (1–5)	2.2	3.4	1.2
Motivation to study programming (1–5)	2.5	3.9	1.4
Conceptual understanding test (overfitting, generalization, data quality), %	1.6	4.3	2.7
Share of students completing the course, %	–	100	–

The main limitations of the study are the small sample size, the absence of a control group, and the reliance on students' self-assessment. Further research should include a comparison with a control cohort and a longitudinal analysis of student performance in subsequent mathematics and programming courses.

Thus, the rapid advancement and democratization of AI create an opportunity to reconsider the foundations of introductory AI education. Rather than teaching beginners a simplified version of a traditional curriculum and postponing meaningful interaction with AI until sufficient prerequisites have been acquired, education can provide early, structured experiences with modern AI technologies and progressively connect those experiences to formal theoretical knowledge. Such an experience-driven approach does not diminish the importance of rigorous foundations; instead, it can provide students with the intuition, motivation, and broader understanding necessary to acquire those foundations more effectively. In this sense, adapting AI education to the modern technological landscape means not merely introducing new technologies into existing courses, but reconsidering how the first meaningful understanding of artificial intelligence is developed.

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