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Educational Artificial Intelligence and Intelligent Tutoring Systems: Foundations, Evolution, and Contributions to Adaptive Learning

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Abstract

This article provides an in-depth analysis of Artificial Intelligence in Education (AIED) and Intelligent Tutoring Systems (ITS), highlighting their theoretical foundations, historical evolution, and contributions to the design of adaptive learning environments. Through a critical review of the scientific literature, the study demonstrates the ability of these technologies to model learners, personalize learning pathways, and enhance the quality of pedagogical feedback. The analysis also reveals a growing convergence between AIED and ITS, particularly with the rise of generative artificial intelligence, which is transforming modes of interaction and opening new perspectives for individualized learning. However, the study also identifies major challenges related to algorithmic bias, data privacy, and the risk of dehumanizing educational practices. These findings call for a rethinking of the integration of these technologies from an ethical, inclusive, and human-centered perspective. Thus, AIED and ITS appear to be promising levers for the renewal of educational practices, provided that they are designed and implemented responsibly.

Keywords: Educational Artificial Intelligence; Intelligent Tutoring Systems; Adaptive Learning; Learner Modeling; Personalization; Generative Artificial Intelligence; Educational Technologies

1. Introduction

The contemporary educational context is characterized by an increasing diversification of learner profiles, learning paces, and learning styles, placing educational institutions in the face of major pedagogical challenges. In digital, hybrid, or fully online learning environments, this heterogeneity is further amplified by the need for teachers to simultaneously provide individualized support while ensuring coherent pedagogical management. This evolution in educational practices has strengthened the demand for technological systems capable of supporting the personalization of learning pathways, improving learner monitoring, and enhancing the overall effectiveness of teaching and learning processes (Woolf, 2010).

Within this perspective, Educational Artificial Intelligence (AIED) and Intelligent Tutoring Systems (ITS) have gradually emerged as promising solutions to address these challenges. Relying on cognitive models, learner modeling mechanisms, and adaptive algorithms, these systems aim to offer learning environments capable of dynamically adjusting content, activities, and feedback according to individual learner needs. However, despite the technological and theoretical advances achieved in this field, their actual capacity to deliver truly effective, pedagogically relevant, and ethically responsible personalization remains a subject of debate (Holmes et al., 2019; Zawacki-Richter et al., 2019).

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Indeed, several questions persist regarding the validity of the models employed, the accuracy of adaptation mechanisms, and the real impact of these systems on learning outcomes. These concerns lead to the formulation of the following central research problem: to what extent does the integration of Educational Artificial Intelligence and Intelligent Tutoring Systems enable the design of learning environments that are genuinely adaptive, effective, and respectful of pedagogical and ethical requirements, while taking into account learner diversity?

Based on this problem statement, the research is structured around several guiding questions intended to frame the analysis. First, it seeks to identify the theoretical, cognitive, and pedagogical models underlying the functioning of AIED and ITS. Second, it examines the extent to which learner modeling and pedagogical adaptation mechanisms allow for truly effective personalization of learning pathways. Finally, the analysis aims to highlight the technical, pedagogical, and ethical limitations of these systems, as well as the conditions necessary for their responsible integration into educational settings.

Within this framework, the primary objective of this article is to conduct an in-depth analysis of the conceptual foundations, evolution, and contributions of Educational Artificial Intelligence and Intelligent Tutoring Systems in order to assess their real potential to support adaptive and personalized learning. This analysis seeks to clarify key concepts, examine learner modeling and pedagogical adaptation mechanisms, and evaluate their contribution to improving the effectiveness of contemporary educational systems, while also shedding light on the challenges, limitations, and ethical issues associated with their implementation.

In line with these objectives, it is necessary to rely on a rigorous theoretical framework that situates the study within its scientific field. An analysis of fundamental concepts, the cognitive models employed, and the major technological developments constitutes an essential step in understanding the dynamics that structure the development of AIED and ITS. The following section is therefore devoted to the presentation of this theoretical framework, which establishes the conceptual foundations necessary for analyzing the contributions and limitations of intelligent learning systems.

2. Theoretical Framework (State of the Art)

2.1. Definition and Foundations of Educational Artificial Intelligence (AIED)

Educational Artificial Intelligence (AIED) is an interdisciplinary field dedicated to the application of artificial intelligence techniques to support, model, and optimize learning and teaching processes. According to Woolf (2010), AIED is based on the integration of methods drawn from machine learning, cognitive modeling, educational psychology, and instructional design, with the aim of developing systems capable of observing and interpreting learners' behaviors. The foundations of AIED include learner modeling, the personalization of learning pathways, performance prediction, and the generation of feedback adapted to users' cognitive and affective needs (Nkambou, Mizoguchi, & Bourdeau, 2010). AIED is not limited to the automation of educational tasks; rather, it seeks to achieve a deep understanding of learning mechanisms in order to provide intelligent, adaptive, and context-aware support.

2.2. Historical Evolution of Educational Artificial Intelligence

The evolution of AIED can be described through four major successive phases reflecting technological advances and methodological shifts. The first phase, beginning in the 1970s, corresponds to the era of symbolic approaches, characterized by the use of expert systems based on explicit rules and logical models of knowledge representation. During the 1990s, a second phase emerged with the development of cognitive models such as ACT-R, which made it possible to simulate learners' mental processes and predict their performance (Anderson et al., 1995). This period gave rise to landmark tools such as the Cognitive Tutor (MATHia) developed by Carnegie Learning.

From the early 2000s onward, a third phase developed with the rise of Educational Data Mining and machine learning, enabling educational systems to analyze large volumes of data, identify behavioral patterns, and adapt instructional interventions based on observed learner behaviors. Finally, since approximately 2015, a fourth phase has emerged with the advent of generative artificial intelligence and advanced language models, (Kasneci et al., 2023; UNESCO, 2023). These technologies introduce unprecedented capabilities for interaction, dialogue, and automated generation of educational content, thereby strengthening opportunities for real-time personalization and adaptation. Platforms such as Duolingo also leverage these technologies to enhance the tutoring experience.

2.3. Definition and Architecture of Intelligent Tutoring Systems (ITS)

Intelligent Tutoring Systems (ITS) are interactive learning environments designed to provide personalized instruction by emulating, as closely as possible, the behavior of a human expert tutor. According to VanLehn (2006), an ITS aims to diagnose the learner's cognitive state, identify errors, anticipate learning needs, and deliver appropriate instructional interventions. ITS are traditionally based on an architecture composed of four complementary models.

The learner model represents the user's knowledge, skills, misconceptions, strategies, and beliefs, evolving dynamically throughout the learning process (Corbett & Anderson, 1995). The domain model contains the structure of the knowledge to be taught, including concepts, rules, procedures, or discipline-specific problem sets. The pedagogical model defines instructional strategies, sequencing decisions, types of feedback, and decision-making rules guiding the system's interventions. Finally, the tutoring interface serves as the communication channel between the system and the learner, enabling multimodal interactions ranging from text-based feedback to spoken dialogue or animated pedagogical agents.

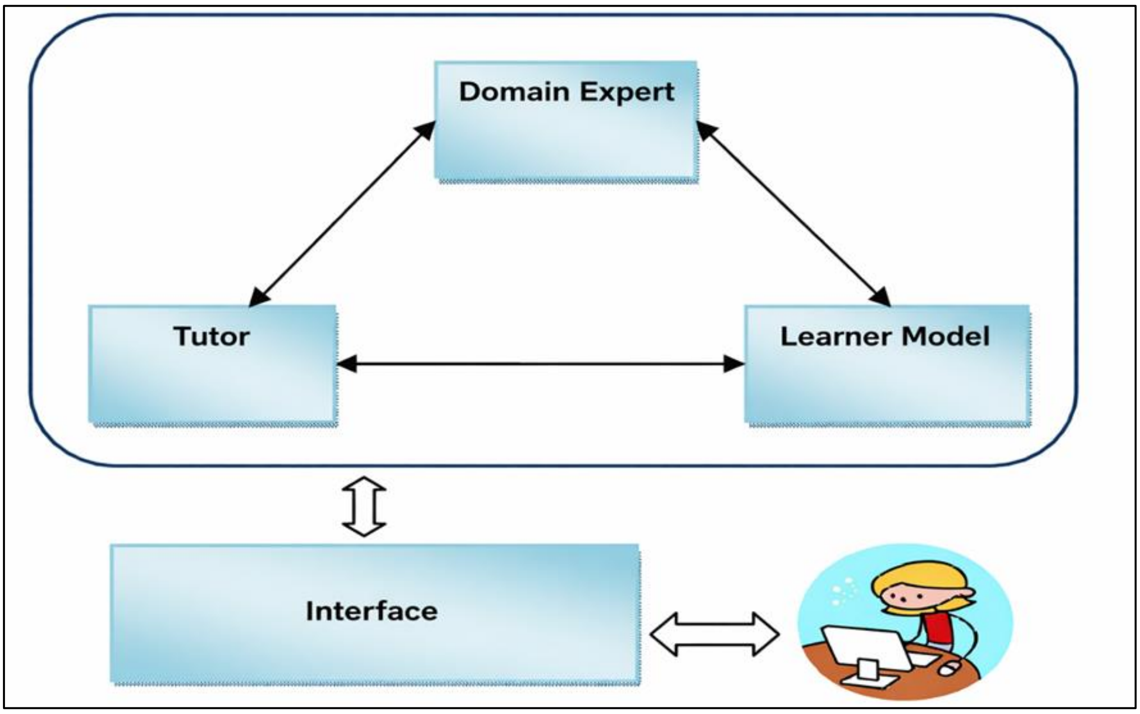

Figure 1 Architecture of an Intelligent Tutoring System (ITS).

Description: The architecture of an Intelligent Tutoring System is based on four interdependent modules. The domain model organizes and structures the body of knowledge to be taught, whether in the form of concepts, rules, or procedures. The learner model represents the user's cognitive state, including their knowledge, beliefs, problem-solving strategies, and difficulties. The pedagogical model determines instructional strategies, the sequencing of learning activities, and the type of feedback to be provided, while the tutoring interface ensures communication between the system and the learner through textual, graphical, or spoken interactions. These modules are coordinated by inference mechanisms that enable the system to adjust its interventions in real time according to the learner's actions and needs.

2.4. Historical Evolution of Intelligent Tutoring Systems

The history of Intelligent Tutoring Systems can also be divided into several successive generations. The first generations, developed during the 1980s, were based on rule-based expert systems, offering structured but relatively inflexible tutoring. The second generation integrated cognitive models, particularly those derived from ACT-R, enabling fine-grained modeling of learners' mental processes and improving the prediction of errors and performance.

The third generation, which emerged in the early 2010s, relies on machine learning techniques such as Bayesian Knowledge Tracing (BKT) and Deep Knowledge Tracing (DKT) to adapt instructional interventions in real time based on the digital traces left by learners. Finally, a current fourth generation of ITS leverages advances in generative artificial intelligence and language models to enable more natural dialogic interaction, enrich system-generated explanations, and enhance the tutor's ability to adapt to diverse pedagogical contexts.

2.5. Convergences between Educational Artificial Intelligence and Intelligent Tutoring Systems

A joint analysis of Educational Artificial Intelligence and Intelligent Tutoring Systems reveals strong convergences, particularly in their objectives and underlying mechanisms. The first convergence lies in the personalization of learning: both fields aim to adapt content, pacing, and instructional strategies according to learners' individual characteristics. This personalization is made possible through knowledge modeling, error prediction, and the ability to adjust learning pathways.

A second convergence concerns dynamic adaptation, a process through which the system continuously modifies its interventions in response to learners' actions or progress. This adaptivity relies on the analysis of learning traces and on algorithms capable of making pedagogical decisions in real time. Finally, a third convergence relates to tutoring interaction, notably through the use of conversational agents and dialog-based systems that provide more engaging, natural, and contextualized support. With the rise of generative artificial intelligence, this interactional dimension is further enhanced, leading to interfaces capable of understanding natural language, explaining concepts, and guiding learners through the resolution of complex problems (Luckin et al., 2016).

2.6. Joint Evolution of Educational Artificial Intelligence and Intelligent Tutoring Systems (1970–2024)

Table 1 Major phases in the development of Educational Artificial Intelligence (AIED) from 1970 to 2024.

Period	Dominant Approach	Key Technologies	Example / Contribution
1970–1980	Symbolic approaches	Expert systems, logical rules	Early rule-based intelligent tutors
1990–2000	Cognitive models	ACT-R, cognitive modelling	Cognitive Tutor (Anderson et al., 1995)
2000–2010	Data-driven and machine learning approaches	Educational Data Mining, BKT	Data-based instructional adaptation
2010–2020	Advanced predictive AI	Deep learning, DKT	Complex adaptive learning systems
2020–2024	Generative AI	GPT-4, Gemini, AI agents	ChatGPT, MATHia, Duolingo AI

This table highlights a gradual transition from symbolic approaches toward hybrid, data-driven, and generative systems, reflecting a paradigm shift in the design of intelligent learning environments.

3. Methodology

The present study adopts a theoretical and analytical review methodology, descriptive, and comparative approach aimed at exploring the conceptual foundations, historical evolution, and integration mechanisms of Educational Artificial Intelligence (AIED) and Intelligent Tutoring Systems (ITS). It is not based on direct experimentation with a sample of learners, but rather on an in-depth critical analysis of the existing scientific literature in the fields of artificial intelligence, cognitive sciences, and educational technologies (Woolf, 2010; Nkambou, Mizoguchi, & Bourdeau, 2010). This approach makes it possible to identify the main dynamics, convergences, and current limitations of intelligent learning systems, while providing a solid conceptual framework for future empirical research, particularly in the design of adaptive learning environments.

3.1. Type of Study

The study is essentially theoretical and aims to provide an in-depth analysis of the concepts and models that structure the fields of Educational Artificial Intelligence and Intelligent Tutoring Systems. It relies on a descriptive approach intended to present in detail the various architectures, methods, and mechanisms characterizing these systems, particularly with regard to learner modeling, pedagogical adaptation, and human–computer interaction (VanLehn, 2006).

A comparative dimension is also adopted in order to contrast classical approaches, based on expert systems and symbolic logic, with more recent approaches grounded in machine learning and generative artificial intelligence

(Anderson et al., 1995; Koedinger & Corbett, 2006). This comparison highlights the major evolutions that have shaped these fields, as well as the associated pedagogical transformations. Furthermore, the research adopts a reflective and critical stance that questions the pedagogical, cognitive, and social implications of the growing introduction of intelligent systems into educational environments (Luckin et al., 2016).

3.2. Sources and Selection Criteria

The sources used in this research are drawn from well-established scientific literature and were selected according to criteria of relevance, validity, and academic impact. Foundational works in Educational Artificial Intelligence and Intelligent Tutoring Systems were prioritized, particularly those addressing cognitive modeling, ACT-R theory, and early intelligent tutors (Anderson et al., 1995; Corbett & Anderson, 1995). These references were complemented by more recent studies published in specialized journals such as Computers & Education, the International Journal of Artificial Intelligence in Education, and IEEE Transactions on Learning Technologies.

Particular attention was given to research focusing on adaptation mechanisms, learning personalization, and the use of generative AI technologies in educational contexts (Woolf, 2010; Luckin et al., 2016). Documents lacking scientific validation or of a purely commercial nature were excluded from the corpus in order to ensure the academic rigor of the analysis.

3.3. Analytical and Structuring Approach

The analysis was conducted in several complementary stages. First, a thorough and critical reading of the selected sources made it possible to identify the main definitions of AIED and ITS, as well as the theoretical models most frequently mobilized in the literature (Nkambou, Mizoguchi, & Bourdeau, 2010; VanLehn, 2006). Second, the information was organized into thematic categories focusing on conceptual foundations, cognitive and computational models, successive generations of tutoring systems, and adaptation mechanisms. Finally, a cross-cutting analysis allowed the identification of major convergences between Educational Artificial Intelligence and Intelligent Tutoring Systems, particularly in terms of personalization, dynamic adaptation, and human–computer interaction, thus forming the basis for the discussion presented below.

4. Results

The results show that AIED and ITS enable advanced personalization of learning pathways through dynamic learner modeling and real-time performance tracking. These systems are capable of identifying conceptual gaps, adjusting the difficulty level of activities, and providing targeted feedback. Empirical studies indicate that learners using intelligent tutoring systems often reduce their learning time while improving performance scores (Anderson et al., 1995).

With regard to interaction, ITS provide immediate, contextualized, and often multimodal feedback (textual, visual, or spoken), which contributes to strengthening conceptual understanding. The introduction of generative artificial intelligence further enhances the quality of this feedback by enabling more detailed, adaptive explanations that more closely resemble those provided by a human tutor.

However, several structural limitations persist. The effectiveness of these systems depends heavily on the availability of high-quality learning data, accurate model calibration, and the transparency of the algorithms used. Complex models, particularly those based on neural networks, pose a “black box” risk, making it difficult to explain system decisions (Kasneci et al., 2023; UNESCO, 2023). Additional challenges relate to the protection of personal data, compliance with legal frameworks (GDPR, AI Act), and inequalities in access to technology.

5. Discussion of Results

The results confirm that Educational Artificial Intelligence and Intelligent Tutoring Systems represent powerful levers for transforming pedagogical practices. Their ability to provide fine-grained learning monitoring, detect errors, and recommend personalized learning pathways constitutes a major asset in a context of increasing learner heterogeneity.

However, this technological performance raises several critical issues:

- Dependence on algorithms may lead to excessive trust in automated, non-explainable recommendations.
- Extreme personalization risks isolating learners by reducing social interactions and diminishing the teacher’s mediating role.

- Model transparency and fairness become essential to ensure responsible adoption.

Consequently, ITS should be designed as tools for pedagogical augmentation rather than as substitutes for professional judgment. Their integration requires robust teacher training, ethical governance, and continuous evaluation of cognitive, social, and organizational impacts.

5.1. Future Perspectives and Recommendations

The results and the ensuing discussion open the way for essential future research and development directions aimed at the responsible integration of AI in education.

Explainable and Transparent AI (XAI): The development of explainable AI models is crucial to ensure that teachers and learners can understand the decisions made by intelligent systems. This transparency is essential for building trust and enabling informed human intervention.

Hybrid Systems and Augmented Pedagogy: The future lies in the design of hybrid systems combining human expertise and artificial intelligence. These tools should aim to augment teachers' pedagogical capacity (classroom tutoring, differentiated instruction) without diminishing their socio-affective support role.

Extended Adaptation and Non-Cognitive Assessment: Future research should focus on the use of AI for inclusion, multicultural adaptation of content, and the assessment of non-cognitive skills such as motivation, resilience, and collaboration.

Recommendations for Responsible Educational AI: It is imperative to establish strict ethical frameworks, including monitoring bias in educational data to ensure equity, safeguarding learner data privacy (GDPR compliance), and training teachers in the critical use of AI tools.

Teacher training in AI constitutes a key lever for the successful integration of these technologies in education. It should enable educators to understand how the tools function, their limitations, pedagogical implications, and associated ethical issues. Such training fosters critical use, promotes meaningful pedagogical integration, and prevents excessive dependence on automated recommendations. It is therefore a necessary condition for responsible adoption, in which AI supports pedagogical action without replacing teachers' professional expertise.

6. Conclusion

In conclusion, Educational Artificial Intelligence and Intelligent Tutoring Systems emerge as major levers for transforming learning environments by offering systems capable of personalizing learning pathways, monitoring learner progress, and adapting content, activities, and pedagogical strategies in real time. The analyses conducted in this article provide elements of response to the initial research problem, namely the extent to which these technologies can support learning that is truly adaptive, effective, and ethical.

The results indicate that, despite certain technical, organizational, and ethical limitations, AIED and ITS constitute powerful tools for addressing learner heterogeneity, optimizing feedback, and enhancing learner engagement, provided that they are deployed in a thoughtful and well-regulated manner. However, their integration cannot be reduced to algorithmic performance alone; it requires constant vigilance regarding bias, data protection, model transparency, and the preservation of the human dimension of pedagogical mediation.

Future perspectives should therefore prioritize the development of hybrid systems combining artificial intelligence and human expertise, the adoption of explainable and responsible approaches, and the integration of multimodal and inclusive learning modalities. The ultimate goal is to design intelligent, sustainable, and learner-centered learning environments capable of supporting learning that is genuinely adaptive and profoundly human.

Compliance with ethical standards

Disclosure of conflict of interest

The authors declare that they have no conflict of interest.

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