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INTELLIGENT AGENTS IN EDUCATIONAL TECHNOLOGIES

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Abstract

Artificial intelligence (AI) is rapidly transforming education, shifting it from static courses to personalized, adaptive learning ecosystems. According to international organizations (including UNESCO), AI is becoming an infrastructural element of higher education; within this frame, intelligent agents (IAs) serve as a mechanism for integrating pedagogical objectives, learner data, and real-time adaptation strategies. This article aims to systematize the architectural and functional principles of using intelligent agents in educational technologies and to analyze implementation practices within contemporary AIEd. We trace the evolution from monolithic Intelligent Tutoring Systems (ITS) to distributed Multi-Agent Systems (MAS) and dialog agents powered by Large Language Models (LLMs). Empirical findings on the effectiveness of classical ITS are synthesized and compared with emerging practices of LLM-based agents on mass-scale platforms. The study's novelty lies in an analytical comparison across three levels—architectural (ITS/MAS), instrumental (dialogic and analytic functions), and institutional (policies and deployment metrics)—grounded in evidence from 2023–2025. In addition, we formulate methodological guidelines for responsible adoption (explainability, fairness, and data protection) to balance automation with pedagogical oversight and to define requirements for scalable, ethical, and transparent learning ecosystems.

Keywords: intelligent agents; Intelligent Tutoring Systems (ITS); Multi-Agent Systems (MAS); adaptive learning; ITS architecture.

БІЛІМ БЕРУ ТЕХНОЛОГИЯЛАРЫНДАҒЫ ИНТЕЛЛЕКТУАЛДЫ АГЕНТТЕР

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Аңдатпа

Жасанды интеллект (ЖИ) білім беру саласын жедел түрлендіріп, оны статикалық курстардан жекелендірілген және бейімделгіш экожүйелерге көшіруде. Халықаралық ұйымдардың (соның ішінде UNESCO) деректеріне сәйкес, ЖИ жоғары білім беру жүйесінің инфрақұрылымдық элементіне айналуда. Осы тұрғыда интеллектуалды агенттер (ИА) педагогикалық мақсаттарды, білім алушылар туралы деректерді және нақты уақыт режиміндегі бейімделу стратегияларын біріктіру тетігі ретінде қарастырылады. Мақаланың мақсаты – интеллектуалды агенттерді білім беру технологияларында қолданудың архитектуралық және функционалдық қағидаттарын жүйелеу және қазіргі заманғы AIEd бағыты аясында енгізу тәжірибелерін талдау. Мақалада монолитті интеллектуалды оқыту жүйелерінен (ИОЖ) таратылған көпагентті жүйелерге (МАЖ) және үлкен тілдік үлгілерге (БТҮ/LLM) негізделген диалогтық агенттерге дейінгі эволюция қарастырылады. Сондай-ақ дәстүрлі ИОЖ тиімділігі бойынша эмпирикалық нәтижелер қорытылады және олар жаппай қолданылатын платформалардағы LLM-агенттердің жаңа тәжірибелерімен салыстырылады. Зерттеудің ғылыми жаңалығы 2023–2025 жылдардағы деректерге сүйене отырып, үш деңгейдегі — архитектуралық (ИОЖ/МАЖ), инструменталдық (диалогтық және аналитикалық функциялар) және институционалдық (саясаттар мен енгізу метрикалары) — аналитикалық салыстыруында. Сонымен қатар, жауапты енгізудің әдістемелік бағдарлары (түсіндіру мүмкіндігі, әділдік, деректерді қорғау) айқындалып, автоматтандыру мен педагогикалық бақылаудың тепе-теңдігін қамтамасыз етуге және ауқымды, этикалық әрі ашық оқу экожүйелеріне қойылатын талаптарды анықтауға бағытталған.

Кілт сөздер: интеллектуалды агенттер; интеллектуалды оқыту жүйелері (ИОЖ); көпагентті жүйелер (МАЖ); бейімделгіш оқыту; ИОЖ архитектурасы.

ИНТЕЛЛЕКТУАЛЬНЫЕ АГЕНТЫ В ОБРАЗОВАТЕЛЬНЫХ ТЕХНОЛОГИЯХ

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Аннотация

Искусственный интеллект (ИИ) ускоренно трансформирует образование, переводя его от статичных курсов к персонализированным и адаптивным экосистемам. По данным международных организаций (в т.ч. UNESCO), ИИ становится инфраструктурным элементом высшей школы; в этой рамке интеллектуальные агенты (ИА) выступают механизмом интеграции педагогических целей, данных об обучающихся и стратегий адаптации в реальном времени. Цель статьи — систематизировать архитектурные и функциональные принципы использования ИА в образовательных технологиях и проанализировать практики внедрения в контексте современного направления AIEd. Рассматривается эволюция от монолитных интеллектуальных обучающих систем (ИОС) к распределённым многоагентным системам (МАС) и диалоговым агентам на базе больших языковых моделей (БЯМ/LLM). Обобщаются эмпирические результаты по эффективности классических ИОС и сопоставляются с новыми практиками LLM-агентов на массовых платформах. Научная новизна состоит в аналитическом сопоставлении трёх уровней: архитектурного (ИОС/МАС), инструментального (диалоговые и аналитические функции) и институционального (политики, метрики внедрения) на материале 2023–2025 гг. Дополнительно формулируются методические ориентиры ответственного внедрения (объяснимость, справедливость, защита данных), обеспечивающие баланс между автоматизацией и педагогическим контролем и задающие требования к масштабируемым, этичным и прозрачным экосистемам обучения.

Ключевые слова: интеллектуальные агенты; интеллектуальные обучающие системы (ИОС); многоагентные системы (МАС); адаптивное обучение; архитектура ИОС.

Introduction

Artificial intelligence (AI) is rapidly transforming educational practices, shifting the focus from static courses to personalized and adaptive learning ecosystems. International organizations emphasize the systemic nature of this shift: UNESCO reports accelerated AI integration in higher education, noting that two-thirds of universities have already developed or are developing guidelines for its use, while nine out of ten faculty members report regular application of AI tools in their professional activities—primarily for research and writing [1-2]. These data indicate that AI has ceased to be an “experimental tool” and has become an infrastructural element of higher education.

Concurrently, the body of empirical and analytical literature supporting AI’s potential to enhance learning outcomes and administrative efficiency is expanding. For example, a global student survey found that 86% of students reported using AI in their studies, with over half using it weekly [3]. The 2024 EDUCAUSE AI Landscape Study similarly highlights how AI and learning analytics are creating prerequisites for reconfiguring educational ecosystems at the course, institutional, and system levels—from adaptive learning trajectories to the transformation of data-driven organizational cultures [4].

By 2023–2025, the momentum has intensified due to the rise of dialogue agents powered by large language models (LLMs). Major platforms illustrate a practical “scaling shift”: for example, Duolingo’s “Max” tier introduced “Explain My Answer” and “Roleplay” features based on GPT-4 (March 14 2023) [5]. These cases demonstrate not only the technological maturity of LLM-agents but also their economic and organizational significance for the EdTech sector [6].

On the policy and regulatory side, the debate has shifted from whether to implement AI to how to implement it safely and responsibly. A recent multi-stakeholder study on responsible AI in education emphasises the need for transparency, explainability and fairness in AI deployment [7].

Within this framework, intelligent agents emerge as a natural mechanism for aligning pedagogical goals, learner data and adaptive strategies. The evolution from monolithic Intelligent Tutoring Systems (ITS) to Multi-Agent Systems (MAS) addresses the challenges of scale and diversity: distributing functions among pedagogical, diagnostic, recommendation and interface agents enables real-time coordination of personalization across content, navigation and learning pace. Simultaneously, LLM-based agents expand the dialogue dimension, compensating for the shortage of individualized tutoring and reducing the transactional costs of supporting large learner cohorts [4, 8].

The significance of this research lies in:

- systematizing the architectural roles of intelligent agents in the transition from classical ITS to MAS;
- integrating empirical evidence of ITS effectiveness with contemporary LLM-based practices on large-scale platforms; and
- formulating methodological guidelines for responsible AI deployment (XAI, privacy, fairness) aligned with international frameworks.

The scientific novelty lies in an analytical comparison across three levels—architectural (ITS/MAS models), instrumental (dialogic and analytical functions of agents), and institutional (policy frameworks and implementation metrics)—based on empirical data from 2023–2025.

Research methods

The purpose of this article is to systematize the architectural and functional principles of using intelligent agents (IA) in educational technologies and to analyze practical implementations and current development trends in Artificial Intelligence in Education (AIEd). To achieve this goal, an analytical comparison was conducted across three key levels of integrating intelligent agents into education: architectural, instrumental, and institutional.

Theoretical and Evidential Basis

The historical foundation for analyzing modern “smart” learning systems draws upon research in Intelligent Tutoring Systems (ITS). The study employed meta-analyses confirming the consistently positive impact of ITS [9] — for instance, Kulik and Fletcher demonstrated a median learning gain of approximately 0.66 standard deviations across 50 controlled evaluations, establishing an empirical foundation for the transition toward multi-agent architectures.

Analytical Approaches

The main research methods included systematization and analytical review, encompassing three complementary perspectives:

- The study systematized the architectural roles of intelligent agents in the transition from classical monolithic ITS structures (comprising domain, student, pedagogical, and interface models) to distributed Multi-Agent Systems (MAS). Special attention was given to the evolution of agent functions—from cognitive support to distributed, cooperative roles, such as detector agents, corrector agents, and observer agents.
- This stage integrated empirical evidence on the effectiveness of classical ITS systems (e.g., COACH, LimTUTOR, RadarMath) with the new practices of dialog-based LLM agents

that emerged between 2023 and 2025. Functional characteristics of multi-agent platforms (MASPLANG, PitchQuest, MEDCO) and their integration with Learning Management Systems (LMS) (Jill Watson, D2L Intelligent Agents) were also examined.

- This analysis focused on policies and regulatory frameworks governing the adoption of AI in education, emphasizing safety, accountability, and ethics. Reports and guidelines from international organizations were reviewed. Based on these sources, methodological guidelines for responsible AI implementation were formulated, including principles of explainability (XAI), algorithmic fairness, and protection of learners' personal data.

Data Sources

The research relied on recent empirical and analytical data (2023–2025), as well as a comprehensive body of academic literature, including reviews published in the Journal of Artificial Intelligence in Education and IEEE Transactions on Learning Technologies, along with proceedings from the AI in Education and IEEE TLT conferences.

Research results

1. Evolution of the Architecture of Intelligent Tutoring Systems: From Classical Models to Multi-Agent Approaches

The development of Intelligent Tutoring Systems (ITS) has been one of the central directions in the evolution of educational technologies. The first systems of this type began to emerge actively in the 1970s–1980s as a logical continuation of Computer-Aided Instruction (CAI) systems — software designed for the automated delivery of learning materials and assessment of student knowledge. However, unlike CAI, which relied on fixed interaction scenarios, ITS introduced a fundamentally new level of adaptivity, capable of modeling the learner's reasoning, errors, and individual cognitive style. Thus, the paradigm shifted from the principle of "the machine transmits knowledge" to "the machine understands and adapts to the learner" [10-11].

At the core of any ITS lies the concept of individualized learning. Research shows that personalized instruction can significantly enhance learning efficiency. According to a meta-analysis by Kulik and Fletcher [9], the use of intelligent tutors improves students' academic performance by an average of 0.66 standard deviations compared to traditional instruction. This effect has been consistently confirmed in reviews published in the Journal of Artificial Intelligence in Education and IEEE Transactions on Learning Technologies, which demonstrate that ITS not only improve knowledge retention but also foster metacognitive skills – the learner's ability to self-assess and self-regulate the learning process.

The architecture of ITS has developed at the intersection of cognitive psychology, pedagogy, and artificial intelligence [12]. An effective ITS must include three key elements: knowledge, dialogue, and the student model. These principles are typically implemented through four interrelated modules, which have become classical components of ITS architecture (see Figure 1).

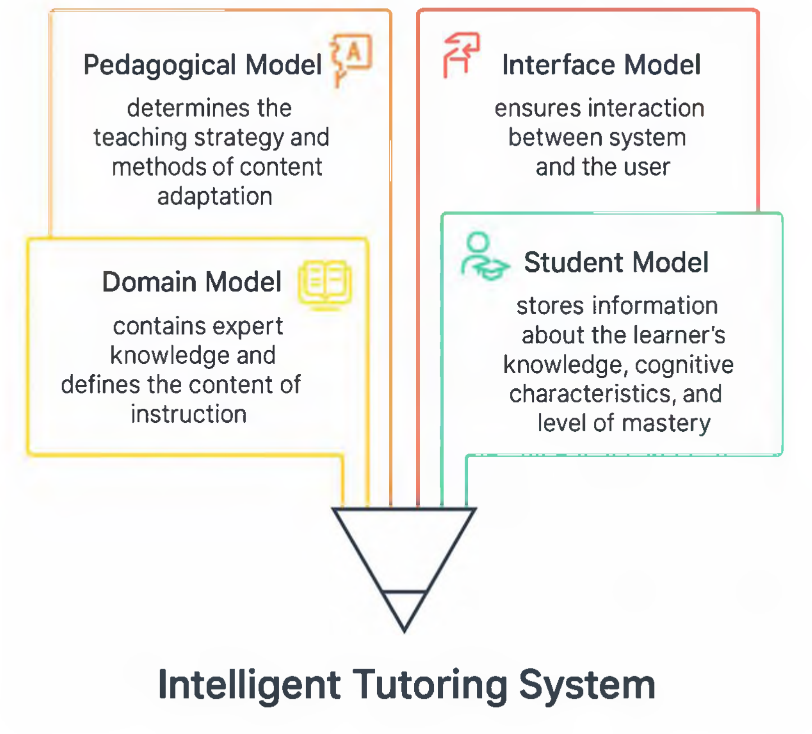

Figure 1. Architecture of an Intelligent Tutoring System

Within this architecture, intelligent agents begin to play a key role — autonomous software entities that perform functions of interaction, analysis, and tutoring. Such agents can act as pedagogical mentors (pedagogical agents), providing feedback and encouragement, or as interface assistants (assistant agents), helping users navigate course materials, manage their learning, and reduce cognitive load. Examples include systems developed under the AutoTutor and Andes Physics Tutor projects, where virtual characters not only assess the correctness of answers but also engage in dialogue with learners, simulating realistic communication scenarios between a student and an instructor.

Intelligent Tutoring Systems (ITS) have the potential to support all levels of cognitive activity identified in Bloom's Taxonomy — from memorization to analysis and synthesis [13]. Such an architecture exerts a comprehensive influence on the learner's cognitive processes, fostering the development of critical thinking and independent problem-solving. ITS also allow instructors to focus on higher-order cognitive tasks while the system handles routine functions such as monitoring and assessment.

However, classical ITS face limitations due to their monolithic structure. All components operate within a single program, which makes the system inflexible when it comes to scalability, knowledge updating, or integration of new tools. In the context of the rapid growth of online education and the diversity of learning environments, such architecture becomes less efficient. According to the OECD Digital Education Outlook [14], the number of students enrolled in online learning platforms has doubled over the past five years, necessitating a transition from centralized models to distributed and self-adaptive systems.

The solution to these challenges has been the shift toward Multi-Agent Systems (MAS), representing a new stage in the evolution of ITS. In multi-agent architectures, individual intelligent agents perform specialized functions — from error diagnosis and recommendation generation to communication management and content adaptation. This modular and distributed design makes the system scalable, flexible, and more resilient to changes in the educational environment. Research presented at AI in Education 2023 and IEEE TLT 2024 shows that using distributed architectures reduces system adaptation time for new users by 30–40%, while the accuracy of task difficulty selection reaches 85–90% [15-20]. Similar results were observed in the implementation of multi-agent platforms such as ActiveMath and MASPLANG [21], where multiple agents collaboratively analyze learner behavior and construct personalized learning trajectories.

Thus, the evolution from classical Intelligent Tutoring Systems to multi-agent models reflects the broader trend of education digitalization — a shift from centralized and static solutions to distributed, adaptive, and cooperative systems. The multi-agent approach combines pedagogical, cognitive, and technical advantages, ensuring a high level of personalization and interactivity. This makes intelligent agents not merely a technological enhancement, but a core instrument in shaping next-generation educational ecosystems, where artificial intelligence acts as a partner to the instructor in achieving shared learning goals.

2. Multi-Agent Systems and Adaptive Learning

The transition from the classical architecture of Intelligent Tutoring Systems (ITS) to Multi-Agent Systems (MAS) has been a natural result of the pursuit of greater adaptivity, scalability, and contextual flexibility in educational technologies. While ITS were built around a centralized model responsible for processing knowledge and making instructional decisions, MAS distribute the management of the learning process among multiple autonomous agents that interact with one another through cooperation and knowledge exchange.

Each intelligent agent within a MAS represents an independent entity with its own goals, knowledge base, and communication mechanisms. In the educational context, these agents perform specialized functions aimed at enhancing learning efficiency and individualization.

Figure 2 presents a classification of modern intelligent agents in education.

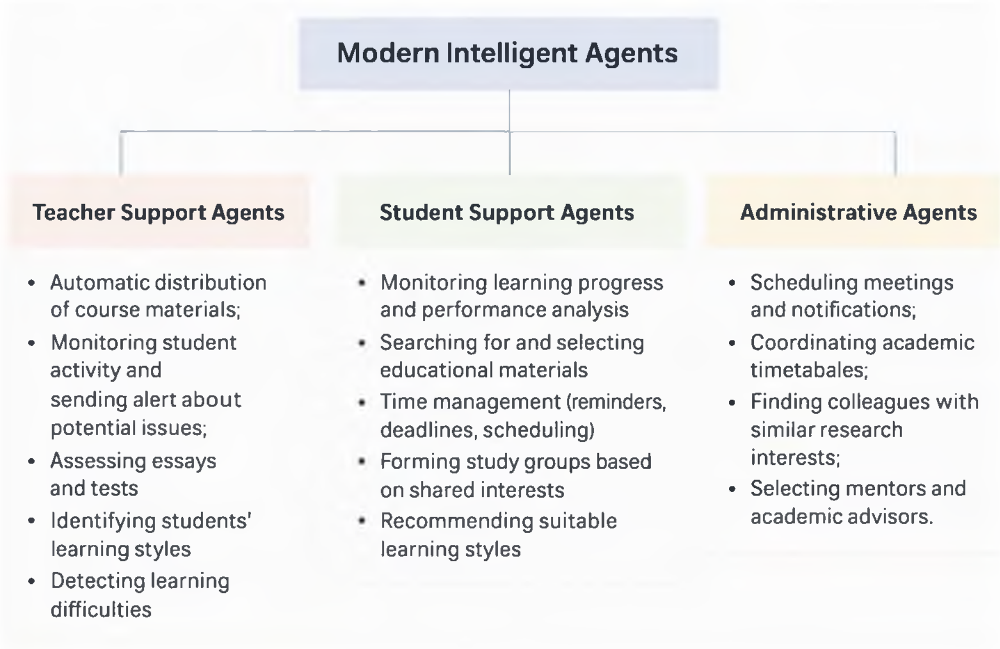

Figure 2. Classification of Modern Intelligent Agents in Education

Interaction among agents occurs through cooperation, knowledge exchange, and dynamic task redistribution, which makes the system more flexible and resilient.

Empirical research confirms the effectiveness of multi-agent architectures. In the ActiveMath system developed in Germany, collaboration among several agents enables the automatic selection of mathematics exercises tailored to students' cognitive styles and error patterns. In the MASPLANG project [21], each agent fulfills a clearly defined role: the User Agent maintains the student model, the Pedagogical Agent manages the instructional strategy, the Exercise Adapter generates adaptive exercises, and Monitor Agents track user actions and assess the learner's knowledge state. The LearnSphere system, implemented in U.S. universities, applies a distributed agent architecture to analyze data on the learning activities of thousands of students, providing timely recommendations and early identification of signs of academic difficulty.

One of the key advantages of multi-agent systems is their ability to provide deep personalization of learning. While adaptation in classical ITS was centralized, in MAS each agent contributes its own aspect of individualization. For example, an Observer Agent records student actions — such as time spent on tasks, number of clicks, and references to help materials or video lessons; a Diagnostic Agent analyzes typical mistakes and updates the learner model; a Motivation Agent assesses engagement and introduces gamified elements (badges, scores, reminders); and a Prediction Agent applies machine learning algorithms such as Decision Tree, Random Forest, or XGBoost to predict the likelihood of successful course completion. The collaboration of these agents creates a closed adaptive loop: observation → analysis → recommendation → action → evaluation. As a result, the system becomes self-learning — it not only adapts to the learner but also improves its own pedagogical strategies based on accumulated interaction data [22-24].

An important feature of multi-agent systems is their ability to account for individual learning styles. Intelligent agents can automatically identify learner preferences based on behavioral patterns — for example, by the type of materials viewed, the duration of interaction with visual elements, or the frequency of access to theoretical content. After identifying a learner's profile, a Recommender Agent constructs an adaptive learning path, offering materials and interaction formats optimized for that cognitive style. Consequently, engagement increases, learning becomes faster, and cognitive load is reduced.

In addition, intelligent agents have become an integral part of the digital infrastructure of distance learning. In modern platforms (e.g., D2L Brightspace), agents automatically monitor student activity, send personalized notifications, motivational messages, and performance improvement tips. They analyze time-series activity data, identify periods of declining engagement, and can automatically alert the instructor with a recommendation to schedule a personal consultation. According to Desire2Learn Insights (2024), the use of such agents increases the likelihood of course completion by 18–22% compared to groups without agent-based support [25-27].

From a pedagogical perspective, an important function of agents is supporting instructors. So-called Digital Teaching Assistants (for example, Jill Watson, developed at the Georgia Institute of Technology) handle routine tasks such as responding to frequently asked questions, sending announcements, managing deadline reminders, analyzing attendance, and grading essays. This frees instructors' time for more meaningful interaction with students requiring individual support. At the same time, Digital Classmates — student-support agents — help manage time, form study groups based on interests, select appropriate resources, and even recommend nearby authorized proctoring centers for exam completion. Some universities have also introduced Digital Secretaries, administrative support agents that coordinate meetings, analyze schedules, and allocate campus resources.

The implementation results of multi-agent systems in education confirm their practical effectiveness. According to IEEE Transactions on Learning Technologies [28] and the AIED Conference [29], the use of MAS increases student retention by 20–35%, reduces course completion time by 15–25%, and improves academic performance prediction accuracy up to 90%. Moreover, both students and instructors report higher satisfaction levels, as interaction with agents is perceived as more personalized and responsive compared to traditional learning management systems.

3. Examples of the Use of Intelligent Agents in Education

The development of intelligent agents in education has led to the creation of a wide range of systems that differ in purpose, architecture, and level of interactivity. Some are focused on cognitive support and adaptive content delivery, while others are designed for automated assessment, instructor assistance, or simulation of professional scenarios.

Table 1 presents the most illustrative examples of such systems, reflecting the evolution of intelligent learning technologies — from classical expert-based systems to multi-agent and dialogue-driven platforms.

Table 1. Examples of systems utilizing intelligent agents in education

System	Purpose	Implementation Features and Agent Functions
Early Developments		
COACH	Teaching programming in Lisp	Models user actions, tracks errors, and provides adaptive hints based on the learner's problem-solving strategy. One of the first examples of cognitive adaptation.
LimTUTOR	Studying function limits	Demonstrates sample solutions, analyzes student reasoning, and offers corrective recommendations. Capable of assessing not only the final answer but also the logic of the solution process.
Second Generation		
RadarMath	Mathematics learning	Automatically evaluates textual and formula-based responses, recognizes multiple equivalent forms of expressions, improving grading objectivity.
MASS (Multi-Agent Scoring System)	Automated essay scoring	Employs a multi-agent architecture including linguistic, semantic, stylistic, and content agents. Their cooperation enhances scoring reliability and reduces algorithmic bias.
Third Generation		
MASPLANG	Hypermedia distance learning system	Includes a pedagogical agent, monitoring agents, an exercise adapter, and virtual characters (SMIT and SONIA) that provide emotionally oriented feedback. Supports content adaptation to learning styles.
PitchQuest	Venture pitch simulation	Learning environment with multiple roles: mentor agents, investor agents, evaluator agents, and a progress agent. Develops skills in public presentation and entrepreneurial thinking.

MEDCO	Medical education	Simulates clinical scenarios with patient, physician, and radiologist agents. Develops clinical reasoning and decision-making under uncertainty.
Modern Solutions		
Jill Watson (Georgia Tech)	Virtual teaching assistant	Responds to student questions, posts announcements, and analyzes message contexts in online courses. Reduces instructor workload and accelerates communication.
D2L Intelligent Agents	LMS for asynchronous learning	Automatically monitors student activity, sends personalized notifications, motivational messages, and reports to instructors. Enhances engagement and student retention.

The presented systems demonstrate different approaches to integrating intelligent agents into the educational process. Early developments focused on modeling students' cognitive activity and adapting task difficulty levels [30-31]. These systems were the first to show that a software environment could function as a tutor capable of addressing individual errors and adjusting to each learner's pace of knowledge acquisition [31].

Second-generation systems expanded this idea by applying natural language processing (NLP) and machine learning methods to automate assessment. As a result, grading time for written and mathematical assignments was significantly reduced, while the consistency of automated evaluations with expert judgments reached 90% or higher [31]. A particularly notable example is the use of a multi-agent structure in MASS, where each subsystem performs its own analytical function, contributing to a balanced and reliable final result [30].

In the third generation, intelligent agents operate collaboratively rather than in isolation, forming a distributed learning ecosystem. MASPLANG adapts content and navigation to individual learning styles, PitchQuest develops business and presentation competencies through realistic simulation, and MEDCO brings learning into the context of professional practice – a critical factor in the training of medical and engineering specialists [30].

Modern solutions demonstrate the integration of intelligent agents into university learning infrastructures. Rather than replacing instructors, these systems enhance their role by providing personalized student support and automating routine administrative tasks. The implementation of such agents has led to a 20–25% increase in student retention rates in online courses and a reduction in instructor workload by up to 30% [32-33].

Discussion

The interpretation of the obtained results indicates that the development of intelligent agents reflects the global trends in the digitalization of education and enhances pedagogical outcomes when implemented responsibly. Multi-agent systems provide a balance between automation and individualization: they handle routine operations – such as monitoring, notifications, and content adaptation – allowing instructors to focus on strategic and motivational aspects of teaching.

The reviewed examples (COACH, LimTUTOR, RadarMath, MASS, MASPLANG, PitchQuest, MEDCO, Jill Watson, D2L Intelligent Agents) demonstrate that the evolution of intelligent agents in education has progressed through three main stages:

- Cognitive tutoring – modeling students' reasoning and adapting task difficulty (COACH, LimTUTOR).
- Automated assessment – applying NLP and machine learning for objective grading (RadarMath, MASS).

• Distributed and dialog-based ecosystems – multi-agent collaboration and simulation of real professional contexts (MASPLANG, PitchQuest, MEDCO).

Modern solutions such as Jill Watson and D2L Intelligent Agents illustrate the integration of AI into LMS infrastructures, where intelligent agents do not replace instructors but augment their capabilities, reducing administrative workload by 25–30% and increasing student retention by 20–25%.

However, the implementation of intelligent agents in education is accompanied by several ethical and organizational challenges. The key issues include:

• Protection of personal data and transparency of decision-making (Explainable AI, XAI);
• Minimization of algorithmic bias in assessment processes;
• Preservation of pedagogical control and human presence in digital learning environments;
• Enhancement of instructors' digital competence.

The following diagram (Table 2) presents the key directions and mechanisms of intelligent agent implementation at each level of the educational system.

Table 2. Recommendations for the Implementation of Intelligent Agents in Education

Goals and Priorities	Key Actions and Mechanisms	Expected Outcomes
Level of Implementation: Universities and Educational Organizations		
1. Formation of an Institutional AIEd Strategy	Develop a "roadmap" for implementation (pilot → scaling → institutionalization); integrate agents with LMS/SIS/LRS (xAPI, Caliper); include AIEd in strategic documents.	Reduction of digital solution fragmentation; sustainable integration of AI into the educational process.
2. Ethical and Legal Standards	Adopt local regulations on responsible AI use; ensure transparency, data protection, and the right to appeal; establish an AIEd Committee.	Increased trust among students and instructors; compliance with international standards (UNESCO, OECD).
3. Data and Analytics Infrastructure	Integrate intelligent agents with analytical dashboards; create a unified system for monitoring engagement and performance.	Ability to predict academic risks and personalize learning pathways.
4. Staff Training	Organize professional development courses on AI applications and Explainable AI (XAI) principles; enhance instructors' digital literacy.	Preparedness of academic staff for hybrid (human–AI) teaching formats.
Level of Implementation: Instructors and Tutors		
1. Hybrid Tutoring	Delegate routine tasks to agents (grading, reminders, initial feedback); maintain focus on critical thinking and student motivation.	Reduction of administrative workload by 25–30%; increased individualization of learning.
2. Pedagogical Oversight and Ethics	Monitor the accuracy of agent recommendations; adjust notification frequency; maintain pedagogical presence in the learning process.	Balance between automation and instructor involvement.

3. Use of Agent Analytics Data	Analyze activity logs and agent reports to refine teaching methods and curricula; identify student learning difficulties.	Improved diagnostic precision and content adaptation quality.
4. Reflective AI Integration	Use AI to develop students' self-assessment and metacognitive skills (error analysis, dialogic explanations, solution comparison).	Development of metacognitive competencies and reflective learning.

Thus, the implementation of intelligent agents at both the institutional and pedagogical levels requires coordinated strategic, methodological, and technological efforts. The university is responsible for establishing the regulatory and infrastructural framework and fostering a culture of responsible AI, while the instructor ensures pedagogical adaptation and maintains a balance between automation and human interaction. The joint realization of these directions creates the foundation for a sustainable, adaptive, and ethical educational ecosystem of AIEd.

Conclusion

The study demonstrates that intelligent agents have become a system-forming element of digital education, ensuring the transition from monolithic Intelligent Tutoring Systems (ITS) to distributed multi-agent ecosystems and, subsequently, to dialog-based solutions based on Large Language Models (LLMs). The evolution path — CAI → ITS → MAS → LLM agents — is accompanied by a qualitative increase in adaptivity, personalization, and resilience of systems when working with large and diverse learner populations.

The classical ITS architecture (domain model, student model, pedagogical model, and interface model) remains the theoretical framework upon which multi-agent mechanisms of cooperation and role distribution are built. This architecture enables the implementation of a continuous learning cycle — observation → analysis → recommendation → action → evaluation — while accounting for learning styles and motivation dynamics. Practical verification demonstrates a wide range of applications — from early tutors (COACH, LimTUTOR) and assessment tools (RadarMath, MASS) to adaptive hypermedia systems (MASPLANG), professional simulations (PitchQuest, MEDCO), and LMS-integrated agents (Jill Watson, D2L Intelligent Agents).

Overall, the findings indicate that intelligent agents are not an add-on to courses but the foundation of modern educational architecture. Their successful implementation relies on the combination of evidence-based pedagogy, transparent engineering, and responsible data policy. When these principles are observed, agent-based systems become a mechanism for augmenting human intelligence, enhancing the quality, accessibility, and human-centered nature of education.

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