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Review Paper

Educational Robotics and Artificial Intelligence in Adaptive Learning: A Review of Current Advances, Challenges, and Research Opportunities

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ABSTRACT

The integration of Artificial Intelligence (AI) and Educational Robotics has created new opportunities for adaptive and personalized learning. Advances in Machine Learning (ML), Deep Learning (DL), Natural Language Processing (NLP), Computer Vision (CV), and Reinforcement Learning (RL) have transformed educational robots into intelligent learning companions capable of adapting to individual learner needs. This review examines the role of AI-driven educational robotics in adaptive learning by synthesizing its theoretical foundations, enabling technologies, architectural frameworks, educational impacts, challenges, and future directions. The review highlights key adaptive learning concepts, including learner modelling, personalization, and continuous feedback, and discusses how AI technologies support intelligent perception, decision-making, and learner adaptation. The findings suggest that AI-driven educational robots can enhance personalized learning, learner engagement, accessibility, and instructional effectiveness. However, challenges related to data privacy, algorithmic bias, scalability, and teacher–robot collaboration remain significant. Future advances in generative AI, multimodal interaction, lifelong learning systems, and immersive technologies are expected to further strengthen the capabilities of educational robotics. Therefore, AI-driven educational robotics represents a promising pathway toward more adaptive, inclusive, and learner-centred education.

Keywords: Educational Robotics; Artificial Intelligence in Education; Adaptive Learning; Personalized Learning; Intelligent Tutoring Systems; Human–Robot Interaction.

1. INTRODUCTION

The rapid advancement of digital technologies has transformed modern educational systems, creating opportunities for more personalized, data-driven, and learner-centred instructional approaches. Among these developments, the convergence of Artificial Intelligence (AI) and Educational Robotics has emerged as a promising paradigm for supporting adaptive learning and enhancing educational outcomes. AI-powered educational robots are increasingly being designed to provide personalized instruction, intelligent tutoring, and real-time feedback, hence addressing the diverse needs of learners in both formal and informal educational environments [1].

Educational robotics has evolved from simple programmable devices into intelligent learning companions equipped with advanced AI technologies such as Machine Learning (ML), Deep Learning (DL), Natural Language Processing (NLP), Computer Vision (CV), and Reinforcement Learning (RL). These technologies enable robots to perceive, interpret, and respond to learners' cognitive, behavioural, and emotional states, supporting dynamic and adaptive learning experiences [1]. Unlike traditional instructional systems that often deliver uniform content to all learners, AI-enabled educational robots can continuously analyse learner interactions and personalize instructional strategies according to individual learning needs. Consequently, educational robotics has expanded beyond technical training and become an important component of learner-centred education.

The growing interest in educational robotics is also associated with its contribution to the development of twenty-first-century skills. Studies have shown that robotics-based learning environments can enhance creativity, critical thinking, collaboration, problem-solving, and computational thinking, particularly within Science, Technology, Engineering, and Mathematics (STEM) education [2]. AI-based educational systems support automated assessment, intelligent tutoring, predictive learning analytics, and personalized feedback mechanisms that improve learner engagement and academic performance [3]. These developments reflect a broader transition from traditional teacher-centred instruction toward adaptive and personalized learning ecosystems.

Adaptive learning has become a central concept in contemporary educational innovation because of its ability to tailor instructional content, learning pathways, and feedback according to learner characteristics. AI-driven adaptive learning systems continuously analyse learner performance, behaviour, and preferences to provide individualized educational experiences. Within this context, educational robots function as embodied adaptive learning agents capable of utilizing multimodal information such as speech, gestures, facial expressions, gaze patterns, and behavioural interactions to assess learner engagement and understanding [4]. Through real-time adaptation and personalized support, these systems have the potential to enhance motivation, improve learning efficiency, and reduce cognitive overload.

Apart from academic performance, AI-driven educational robotics has significant implications for educational accessibility and inclusion. By adapting instructional strategies to diverse learner profiles, these technologies can support learners with different cognitive abilities, learning preferences, linguistic backgrounds, and special educational needs [5]. Such capabilities align closely with the objectives of the United Nations Sustainable Development Goal 4 (SDG 4), which emphasizes inclusive, equitable, and quality education for all learners [6]. Consequently, the integration of AI and educational robotics represents not only a technological advancement but also a pathway toward more accessible and responsive educational environments.

Despite these valuable contributions, several research gaps remain. First, most existing reviews examine AI in education, adaptive learning, and educational robotics as separate research domains, resulting in fragmented understanding of their interrelationships. Second, many earlier reviews were conducted before the widespread adoption of generative AI, large language models (LLMs), multimodal learning analytics, affective computing, and reinforcement learning–based educational systems [7]. Third, limited attention has been given to architectural frameworks that integrate perception, learner modelling, adaptive decision-making, and feedback mechanisms within intelligent educational robots [8]. Finally, challenges related to algorithmic fairness, privacy, explainability, accessibility, scalability, and teacher–robot collaboration remain insufficiently synthesized across the literature [9].

To address these gaps, this review provides an integrated examination of educational robotics and artificial intelligence in adaptive learning. Specifically, it synthesizes theoretical foundations, AI technologies, educational robotic architectures, pedagogical applications, educational impacts, ethical considerations, and emerging research directions. By bringing together these interconnected research streams, the review aims to provide a comprehensive understanding of the current state of AI-driven educational robotics and identify opportunities for future research and development.

This review is guided by the following research questions:

- **RQ1:** What are the theoretical foundations of adaptive learning that support AI-driven educational robotics?
- **RQ2:** Which AI technologies are most employed in educational robotics, and how do they contribute to adaptive and personalized learning?
- **RQ3:** How do educational robots perceive, model, and respond to learner characteristics through adaptive learning architectures?
- **RQ4:** What educational benefits and learning outcomes have been reported from AI-driven educational robotics?
- **RQ5:** What technical, pedagogical, and ethical challenges are associated with the adoption of AI-enabled educational robotics?
- **RQ6:** What emerging trends and future research opportunities are shaping the next generation of intelligent educational robots and adaptive learning systems?

The remainder of this review is organized as follows. Section 2 presents the foundations of adaptive learning. Section 3 discusses the evolution and applications of educational robotics. Section 4 reviews the AI technologies that enable adaptive educational robotics. Section 5 examines architectural frameworks for AI-driven educational robotics. Section 6 highlights their educational benefits and impacts. Section 7 discusses key challenges, ethical considerations, and future research directions. Finally, Section 8 concludes the review.

2. Adaptive Learning: Concepts and Frameworks

Adaptive learning has emerged as a central paradigm in modern educational technology, driven by the increasing demand for personalized and learner-centred instruction. Unlike traditional educational approaches that follow fixed instructional pathways, adaptive learning systems dynamically adjust content, learning sequences, assessments, and feedback according to individual learner characteristics, performance, and educational needs. Advances in AI, learning analytics, and data-driven decision-making have further accelerated the development of adaptive learning environments capable of delivering personalized educational experiences at scale [10].

The fundamental premise of adaptive learning is that learners differ in prior knowledge, cognitive abilities, learning pace, motivation, and learning preferences. Consequently, uniform instructional approaches may fail to meet the needs of diverse learners. Adaptive learning systems address this challenge by continuously collecting and analysing learner data to generate individualized learning experiences. Through ongoing monitoring of learner interactions and performance, these systems can modify instructional strategies, recommend learning resources, and provide targeted support to improve learning effectiveness and engagement [11].

A key characteristic of adaptive learning is personalization, which enables educational systems to tailor instructional experiences to individual learners. Personalization is achieved through learner modelling, a process that involves constructing and continuously updating representations of learner knowledge, skills, preferences, engagement levels, and learning progress [12]. Learner models serve as the foundation for adaptive decision-making by enabling educational systems to identify knowledge gaps, estimate learner competence, and determine appropriate instructional interventions. As learner profiles evolve over time, adaptive systems can dynamically adjust learning pathways, instructional pace, feedback mechanisms, and assessment strategies according to individual needs [13]. The literature consistently highlights the positive educational impact of personalization and learner modelling. Adaptive learning environments capable of accurately representing learner characteristics have been associated with improved academic performance, enhanced learner motivation, greater knowledge retention, and increased learner autonomy [14]. Furthermore, personalized feedback and progress monitoring support self-regulated learning by helping learners identify strengths, address weaknesses, and make informed decisions about their learning strategies [15]. As AI technologies continue to advance, learner models have evolved from relatively static representations into dynamic and continuously updated frameworks capable of supporting real-time adaptation and intelligent instructional decision-making.

The theoretical foundations of adaptive learning are strongly influenced by cognitive and behavioural learning theories. Cognitive Load Theory (CLT) emphasizes the importance of managing cognitive resources by balancing instructional complexity and learner capacity [16]. Adaptive systems apply this principle by adjusting task difficulty, pacing, and content presentation to minimize cognitive overload while maintaining appropriate levels of challenge. Constructivist perspectives, particularly those associated with Piaget, further emphasize that learners actively construct knowledge through exploration, interaction, and problem-solving. Consequently, adaptive learning environments increasingly encourage active engagement and experiential learning rather than passive content consumption.

Another influential framework is Vygotsky's Zone of Proximal Development (ZPD), which proposes that learning is most effective when instructional support is aligned with a learner's developmental readiness [17]. Adaptive systems operationalize this concept by providing personalized scaffolding based on learner competence levels. As learners develop greater proficiency, instructional support can be gradually reduced, promoting independence and mastery. In contrast, behavioural learning theories emphasize observable learner actions and the role of reinforcement in shaping learning outcomes. Derived from Skinner's behaviourist principles, adaptive systems frequently incorporate feedback, rewards, progress indicators, and gamification mechanisms to reinforce positive learning behaviours and maintain learner motivation [18].

Contemporary adaptive learning systems increasingly integrate cognitive and behavioural perspectives to create more comprehensive learning environments. Cognitive models help explain how learners process and construct knowledge, while behavioural models provide mechanisms for monitoring engagement and reinforcing productive learning behaviours. AI-driven technologies further enhance these theoretical foundations by enabling systems to analyse learner interactions, estimate cognitive states, identify misconceptions, and predict future performance in real time [17].

A defining feature of adaptive learning is the use of continuous feedback loops and adaptive learning pathways. Feedback loops function as self-regulating mechanisms through which learner performance data are collected, analysed, and used to guide instructional decisions [19]. Unlike traditional educational settings where feedback may be delayed, adaptive systems provide timely and individualized responses in the form of hints, recommendations, explanations, corrective guidance, and performance summaries [20]. Such feedback supports knowledge acquisition, learner engagement, and continuous improvement.

Adaptive pathways extend this concept by enabling learners to follow personalized instructional trajectories rather than predetermined sequences. Learners demonstrating mastery can progress to more advanced content, whereas those experiencing difficulties may receive additional support, alternative explanations, or remedial activities. This approach aligns closely with mastery learning principles and contributes to both educational effectiveness and equity by accommodating diverse learner needs [21]. AI technologies further enhance adaptive pathways through predictive analytics and intelligent tutoring mechanisms capable of identifying learning patterns and recommending personalized interventions before difficulties become significant barriers to learning.

The relevance of adaptive learning extends beyond conventional digital learning environments and provides the pedagogical foundation for modern educational robotics. Educational robots increasingly function as embodied adaptive learning agents capable of monitoring learner behaviour, interpreting cognitive and emotional states, and providing personalized instructional support in real time. Like adaptive learning systems, educational robots utilize learner models, adaptive feedback mechanisms, and AI-driven decision-making processes to support individualized learning experiences.

Recent advances in Machine Learning, Natural Language Processing, Computer Vision, and multimodal analytics have strengthened the integration of adaptive learning and educational robotics. These technologies enable robots to analyse speech, gestures, facial expressions, gaze patterns, and behavioural interactions to assess learner engagement and understanding. Based on these observations, educational robots can adapt instructional strategies, modify task difficulty, provide personalized feedback, and offer motivational support. Consequently, educational robots have evolved from simple instructional tools into intelligent learning companions capable of supporting personalized and learner-centred education.

In summary, adaptive learning represents a transformative approach that shifts education from standardized instruction toward personalized learning ecosystems. Through learner modelling, cognitive and behavioural adaptation, continuous feedback, and AI-driven decision-making, adaptive learning systems can respond dynamically to diverse learner needs while improving engagement, performance, and self-regulated learning. These principles provide the theoretical and pedagogical foundation for AI-driven educational robotics, which increasingly leverage adaptive learning mechanisms to create intelligent, responsive, and personalized educational experiences.

3. Foundations of Educational Robotics

Educational Robotics has emerged as a multidisciplinary field that integrates education, computer science, artificial intelligence, engineering, and cognitive science to support teaching and learning. Over the past several decades, educational robotics has evolved from a specialized tool for teaching programming and engineering concepts into a broader educational paradigm that promotes experiential, collaborative, and learner-centred learning. Recent advances in AI have further expanded the capabilities of educational robots, enabling them to function not only as programmable devices but also as intelligent learning companions capable of supporting adaptive and personalized educational experiences [22].

Educational robotics is generally defined as the design, development, and application of robotic systems for educational purposes. These systems can serve multiple roles within learning environments, including instructional tools, collaborative learning partners, tutors, facilitators, and platforms for hands-on experimentation [22]. Unlike conventional educational technologies that rely primarily on screen-based interaction, educational robots provide embodied and interactive learning experiences that encourage learners to engage directly with physical systems. Such interactions have been associated with increased engagement, active learning, and improved knowledge construction.

A major contribution of educational robotics lies in its ability to support the development of twenty-first-century competencies. Robotics-based learning environments encourage learners to engage in problem-solving, critical thinking, creativity, collaboration, communication, and computational thinking activities that are increasingly important in modern educational and professional contexts [2]. Through designing, programming, testing, and refining robotic systems, learners are required to apply theoretical concepts in authentic situations, thereby fostering deeper understanding and higher-order cognitive skills. Consequently, educational robotics has become closely associated with STEM education and project-based learning approaches.

The theoretical foundations of educational robotics are strongly influenced by constructionist learning principles introduced by Seymour Papert, which emphasize learning through active creation, experimentation, and problem-solving [23]. Early educational robotics platforms, such as the Logo Turtle, demonstrated how physical interaction with programmable systems could support conceptual understanding, logical reasoning, and computational thinking [24]. These early initiatives established the pedagogical foundations of educational robotics and highlighted the value of learning through making and exploration.

As computing technologies became more accessible, educational robotics expanded beyond experimental learning environments and entered mainstream educational practice. The introduction of modular robotics kits, particularly LEGO Mindstorms, significantly reduced technical barriers and enabled wider adoption of robotics-based learning activities [2]. These platforms combined programmable hardware with user-friendly development environments, making robotics accessible to learners with diverse technical backgrounds. Subsequent growth in robotics competitions, maker spaces, and collaborative learning initiatives further accelerated adoption by providing authentic contexts for applying scientific, mathematical, and engineering concepts.

The educational applications of robotics have expanded considerably over time. While STEM education remains one of the most extensively studied application areas, contemporary educational robotics research encompasses a broad range of learning contexts. In STEM disciplines, robots support hands-on experimentation, engineering design, computational thinking, and interdisciplinary problem-solving. Research consistently reports positive effects on learner engagement, conceptual understanding, and analytical reasoning skills.

Beyond STEM education, educational robots have increasingly been employed to support language learning, communication development, and social interaction. Socially interactive robots can engage learners in conversational activities, pronunciation practice, and language immersion experiences while providing immediate and individualized feedback. Studies suggest that such interactions can improve learner confidence, participation, and willingness to communicate, particularly among younger learners and language beginners [22].

Educational robotics has also demonstrated considerable promise in inclusive and special-needs education. Robots have been utilized to support learners with autism spectrum disorder and other developmental or learning challenges by providing structured, predictable, and non-judgmental interactions. Research indicates that robot-assisted interventions can enhance attention, engagement, communication, and social skills, highlighting the potential of educational robotics to promote accessibility and inclusion [22].

Another important application area is collaborative and project-based learning. Educational robots frequently serve as focal points for group activities that require learners to work together to design, program, and troubleshoot robotic systems. Such experiences promote teamwork, communication, leadership, and shared problem-solving while aligning closely with constructivist and experiential learning theories [24]. These collaborative learning opportunities contribute to the broader educational value of robotics beyond technical skill development.

Recent advances in AI have transformed educational robotics from programmable instructional tools into intelligent educational agents capable of supporting adaptive learning. AI technologies such as ML, NLP, CV, and learner analytics enable educational robots to interpret learner behaviour, recognize engagement patterns, provide personalized feedback, and adapt instructional strategies in real time [22]. As a result, educational robots are increasingly capable of supporting personalized and learner-centred learning experiences.

The convergence of educational robotics and adaptive learning has become a significant area of research. Adaptive learning environments seek to accommodate individual learner differences by continuously monitoring performance, identifying learning needs, and modifying instructional strategies accordingly [10]. Educational robots provide a unique platform for implementing these principles because they combine physical embodiment, social interaction, and computational intelligence within a single learning system. Unlike traditional adaptive learning platforms, robots can utilize multimodal communication channels including speech, gestures, facial expressions, and behavioural observations to create richer and more interactive learning experiences [4].

A key component of adaptive educational robotics is learner modelling. Similar to adaptive learning systems, educational robots construct dynamic representations of learner knowledge, skills, preferences, engagement levels, and emotional states [15]. These learner models guide instructional decision-making by enabling robots to adjust task difficulty, provide personalized feedback, recommend learning activities, and offer appropriate levels of support. Continuous feedback loops further enhance adaptation by allowing robots to evaluate learner performance, identify misconceptions, and provide corrective guidance in real time [19].

The integration of AI technologies has further strengthened the adaptive capabilities of educational robots. Machine learning algorithms can identify learning patterns and predict learner needs, while NLP enables conversational tutoring and personalized dialogue. Computer Vision systems allow robots to interpret facial expressions, gaze direction, and body language to estimate engagement and emotional states [1]. Together, these technologies enable educational robots to respond dynamically to both cognitive and affective aspects of learning.

Despite substantial progress, several challenges remain. Research suggests that educational outcomes depend not only on robotic technologies but also on instructional design, curriculum integration, teacher expertise, and learning context [2]. While many studies report improvements in engagement, motivation, and skill development, evidence regarding long-term academic achievement remains mixed. Furthermore, issues related to scalability, accessibility, privacy, and ethical implementation continue to influence the adoption of educational robotics in practice.

Altogether, this literature demonstrates that educational robotics has evolved from programmable learning tools into intelligent and adaptive educational systems. By combining experiential learning, social interaction, learner modelling, adaptive feedback, and AI-driven decision-making, educational robots increasingly support personalized and learner-centred education. This convergence of robotics, artificial intelligence, and adaptive learning provides the foundation for understanding the technological developments discussed in the following section on AI in educational robotics.

4. Theoretical and Technological Foundations of AI in Educational Robotics

4.1 Evolution of AI in Educational Robotics

The integration of AI into educational robotics reflects the convergence of intelligent computing, adaptive learning, and human–robot interaction. Over the past several decades, AI has transformed educational technologies from static instructional systems into intelligent environments capable of personalization, adaptive feedback, and data-driven decision-making. This transformation has significantly expanded the capabilities of educational robots, enabling them to function as adaptive learning companions rather than programmable instructional tools.

The origins of AI in education can be traced to early Intelligent Tutoring Systems (ITS) such as Scholar and Project PLATO, which demonstrated the potential of AI to model learner knowledge and provide individualized instructional support [25]. During the 1980s, expert systems further advanced educational technologies by introducing rule-based guidance and domain-specific recommendations, although their adaptability remained limited [26]. The emergence of machine learning and data-driven approaches later enabled educational systems to analyse learner behaviour, predict performance, and personalize instruction based on observed interactions [27].

Recent advances in ML, DL, NLP, CV, and conversational AI have accelerated the evolution of educational robotics. Modern educational robots can process multimodal learner data, interpret language and behaviour, provide adaptive feedback, and support personalized learning pathways in real time [28]. Consequently, AI has become the technological foundation for intelligent and learner-centred educational robotics.

4.2 Machine Learning and Deep Learning for Adaptive Learning

ML and DL are among the most influential technologies supporting adaptive learning systems. By analysing learner interactions, performance data, and behavioural patterns, ML algorithms can identify learning needs, predict outcomes, and recommend personalized instructional interventions [29]. These capabilities enable educational systems to move beyond one-size-fits-all instruction and support individualized learning pathways.

A major contribution of ML is learner modelling. Through the analysis of assessment results, interaction histories, and learning trajectories, ML techniques generate dynamic learner profiles that capture knowledge levels, misconceptions, engagement patterns, and learning progress. Such profiles enable adaptive systems to determine appropriate instructional strategies and provide targeted support.

DL extends these capabilities by processing complex and multimodal data sources such as text, speech, video, and sensor information. DL models can identify subtle patterns in learner behaviour, estimate engagement, and improve predictive accuracy for educational decision-making [29]. Educational platforms such as ALEKS and DreamBox Learning illustrate how AI-driven personalization can support mastery learning and adaptive instruction [30].

Within educational robotics, ML and DL enable intelligent decision-making, speech recognition, emotion detection, gesture interpretation, and adaptive interaction. However, challenges related to data quality, transparency, fairness, and algorithmic bias remain important considerations for the responsible deployment of AI-driven educational systems. Overall, ML and DL serve as core technologies that support learner modelling, personalization, and adaptive educational experiences.

4.3 Natural Language Processing for Human–Robot Interaction

NLP enables educational robots to communicate with learners through natural language, facilitating conversational tutoring, personalized feedback, and learner-centred interaction. Unlike traditional educational interfaces that rely on predefined commands, NLP-powered robots can engage in dialogue, answer questions, provide explanations, and adapt communication styles according to learner needs [31].

Within adaptive learning environments, NLP contributes significantly to personalization by analysing learner responses and identifying knowledge gaps, misconceptions, and engagement levels. Conversational interactions provide valuable information that can be incorporated into learner models, allowing educational robots to tailor instructional support in real time.

Recent advances in large language models and conversational AI have further enhanced the capabilities of educational robots. Modern NLP systems can maintain context-aware conversations, generate personalized explanations, and support complex educational tasks across diverse domains [7]. Applications include language learning, literacy development, intelligent tutoring, and problem-solving support.

Despite these advances, NLP systems face challenges related to ambiguity, multilingual communication, contextual understanding, and potential inaccuracies in AI-generated responses. Issues of privacy, transparency, and ethical use of learner conversations also require careful consideration. Nevertheless, NLP remains a key technology for creating more interactive, responsive, and human-like educational robots.

4.4 Computer Vision and Affective Perception

CV and affective perception technologies enable educational robots to observe and interpret learner behaviour, engagement, and emotional states. In adaptive learning environments, effective personalization requires more than performance assessment; it also depends on understanding how learners interact, respond, and feel during learning activities [32].

CV systems analyse facial expressions, gaze direction, gestures, posture, and other visual cues to generate insights into learner behaviour. One important application is engagement detection, where visual indicators are used to estimate attention levels and participation. Educational robots can use this information to adjust instructional pacing, provide additional support, or introduce motivational interventions when disengagement is detected [33].

Affective perception extends these capabilities by enabling robots to recognize emotions such as confusion, frustration, boredom, interest, and satisfaction [41]. Such information allows educational robots to adapt instructional strategies according to both cognitive and emotional learner needs. Recent advances in deep learning have improved the accuracy of emotion recognition, facial analysis, and behavioural interpretation, contributing to more responsive and personalized educational experiences [29].

The integration of CV with NLP and ML supports multimodal learner understanding and richer personalization. However, privacy concerns, cultural variations in emotional expression, and ethical considerations remain important challenges. Despite these limitations, CV and affective perception significantly enhance the adaptive capabilities of educational robotics.

4.5 Reinforcement Learning for Adaptive Educational Robotics

Reinforcement Learning (RL) has emerged as a promising approach for adaptive educational systems because it enables intelligent agents to learn effective instructional strategies through interaction and feedback. Unlike supervised learning, RL focuses on optimizing sequential decision-making by learning policies that maximize long-term educational outcomes.

Within adaptive learning environments, learner performance, engagement, and task completion serve as feedback signals that guide instructional adaptation. RL-based systems can dynamically select learning activities, adjust difficulty levels, provide hints, and personalize feedback according to evolving learner needs. This makes RL particularly suitable for adaptive learning, where instructional decisions must continuously respond to changing learner states [34].

Educational robotics provides a natural application domain for RL because robots operate in dynamic and interactive learning environments. Through repeated interactions, robots can learn when to provide encouragement, increase challenge, offer remediation, or modify communication strategies. Recent developments in Deep Reinforcement Learning (DRL) have further expanded these capabilities by enabling the integration of multimodal learner data such as speech, facial expressions, and behavioural observations.

Although RL offers significant potential for personalization and adaptive decision-making, challenges remain regarding reward design, interpretability, learner safety, and the large number of interactions often required for training. Nevertheless, RL represents an important step toward intelligent educational systems capable of continuously improving instructional effectiveness through experience [35].

4.6 Toward Multimodal and Intelligent Educational Robots

Recent research increasingly emphasizes the integration of multiple AI technologies into unified educational robotics systems. Rather than relying on isolated technologies, modern educational robots combine Machine Learning, Deep Learning, Natural Language Processing, Computer Vision, affective computing, and Reinforcement Learning to create multimodal and intelligent learning environments.

Multimodal educational robots can process information from diverse sources, including speech, text, facial expressions, gestures, behavioural interactions, and assessment outcomes. This capability enables more comprehensive learner modelling and supports personalization across both cognitive and affective dimensions of learning. NLP facilitates communication, CV enables perception, ML and DL support learner analytics, and RL optimizes adaptive decision-making [36]. Together, these technologies allow educational robots to observe, understand, and respond to learner needs more effectively than traditional educational systems.

The emergence of large language models, multimodal foundation models, and generative AI has further accelerated progress toward intelligent educational robots capable of contextual reasoning, personalized explanation, and adaptive support [37]. As a result, educational robots are increasingly being viewed as intelligent learning companions rather than simple instructional tools.

Despite substantial progress, challenges related to interoperability, computational complexity, privacy, transparency, bias, and responsible AI remain significant. Nevertheless, the convergence of multimodal AI technologies is laying the foundation for next-generation educational robots capable of delivering highly personalized, adaptive, and learner-centred educational experiences. These technological developments provide the basis for the architectural frameworks discussed in the following section.

5. Architecture for AI-Driven Educational Robotics

5.1 Perception–Planning–Action Framework

The Perception–Planning–Action (PPA) framework is one of the most widely adopted architectural models for AI-driven educational robotics. Derived from intelligent agent and autonomous robotics research, the framework enables educational robots to observe learner behaviour, interpret learning contexts, make instructional decisions, and deliver adaptive responses in real time [38]. By integrating perception, planning, and action within a continuous feedback cycle, the PPA architecture provides the foundation for personalized and adaptive learning environments.

The perception layer serves as the interface between the learner and the robotic system. Through sensors and AI technologies, educational robots collect information about learner performance, engagement, emotional states, and environmental conditions. Modern perception systems integrate

Computer Vision, Natural Language Processing, speech recognition, and multimodal sensing technologies to capture both cognitive and affective indicators of learning. These capabilities allow robots to identify misconceptions, monitor progress, and assess learner engagement.

Information acquired through perception is processed by the planning layer, where learner models, pedagogical objectives, and AI algorithms are used to determine appropriate instructional actions [39]. Machine Learning and Deep Learning techniques support learner analytics and performance prediction, while Reinforcement Learning enables continuous optimization of instructional strategies. Consequently, planning modules can adapt learning pathways, task difficulty, feedback mechanisms, and support strategies according to learner needs.

The action layer translates instructional decisions into educational interventions. Educational robots may provide explanations, personalized feedback, hints, demonstrations, motivational support, or collaborative learning activities depending on the learner's current state and learning objectives [40]. Through socially interactive behaviours and conversational interfaces, robots can deliver instructional support in ways that resemble human tutoring.

A key strength of the PPA framework is its support for continuous adaptation. Feedback generated during educational interactions is reintroduced into subsequent perception cycles, allowing robots to evaluate instructional effectiveness and refine future decisions. As AI technologies continue to evolve, the integration of NLP, CV, ML, and RL within PPA architectures is transforming educational robots into intelligent learning companions capable of supporting cognitive, behavioural, and emotional aspects of learning.

5.2 Adaptive Decision Making

Adaptive decision making represents the core intelligence of educational robotics, enabling robots to transform learner information into personalized instructional actions. Acting as the bridge between perception and instructional delivery, adaptive decision-making systems continuously analyse learner performance, engagement, emotional states, and learning progress to determine the most appropriate educational intervention [39].

Central to this process is learner modelling, which provides structured representations of learner knowledge, skills, preferences, misconceptions, and behavioural characteristics. These learner models enable educational robots to estimate learning states, predict future needs, and personalize instructional support according to individual learner requirements [40]. As learner models are continuously updated, educational decisions can evolve dynamically throughout the learning process.

Recent advances in ML and DL have significantly improved adaptive decision-making capabilities. AI-driven systems can identify complex patterns in learner data, predict performance, and recommend personalized interventions before learning difficulties become significant barriers [29]. RL further extends these capabilities by enabling robots to learn effective teaching strategies through interaction and feedback rather than relying solely on predefined instructional rules. Through continuous optimization, RL-based systems can refine instructional policies and improve educational outcomes over time.

Another important trend is the integration of pedagogical reasoning into decision-making processes. Effective educational adaptation requires consideration of learning objectives, cognitive development, motivation, and instructional theory in addition to data analytics [41]. Modern educational robots increasingly combine AI-driven personalization with pedagogical principles to ensure that adaptive decisions remain educationally meaningful. Furthermore, affect-aware decision making allows robots to respond differently to learner emotions such as confusion, frustration, boredom, or high engagement, thereby enhancing both cognitive and emotional support.

Despite significant progress, challenges remain regarding transparency, fairness, explainability, and ethical use of AI-driven decisions. Nevertheless, adaptive decision making remains a fundamental component of intelligent educational robotics, enabling highly personalized and responsive learning experiences.

5.3 Continuous Feedback and Learner Modelling

Continuous feedback and learner modelling form the adaptive core of educational robotics by enabling systems to monitor learner progress, evaluate instructional effectiveness, and refine personalization strategies over time [41]. These mechanisms allow educational robots to maintain an evolving understanding of learners and continuously adapt educational interactions according to changing learner characteristics.

Learner modelling involves the construction of computational representations of learner knowledge, skills, preferences, engagement levels, and emotional states. These models provide the informational basis for adaptive instructional decisions and support personalized learning experiences. While early systems relied on relatively static learner profiles, contemporary educational robots employ AI technologies to maintain dynamic learner models that continuously evolve through interaction.

Modern learner modelling increasingly incorporates multimodal data obtained from assessment results, conversational interactions, behavioural observations, and emotional indicators. Machine Learning, Deep Learning, Natural Language Processing, and Computer Vision enable robots to analyse these diverse information sources and generate richer representations of learner states [29]. Such multimodal approaches provide a more comprehensive understanding of learning processes than traditional performance-based assessment alone.

Continuous feedback mechanisms ensure that learner models remain accurate and relevant. During educational interactions, learner responses, engagement patterns, and performance data are continuously collected and analysed. This information enables educational robots to evaluate the effectiveness of instructional interventions and modify teaching strategies when necessary [20]. Personalized feedback may include hints, explanations, corrective guidance, motivational support, or adaptive scaffolding tailored to individual learner needs.

Recent research highlights the transition from static performance monitoring to multimodal learner modelling that integrates cognitive, behavioural, linguistic, and affective dimensions of learning [32]. Reinforcement Learning further strengthens this process by enabling robots to evaluate feedback outcomes and refine instructional policies over time. This creates a self-improving adaptive cycle in which learner understanding and instructional effectiveness continuously evolve through interaction.

The challenges related to data quality, privacy, transparency, and interpretability remain important considerations. Nevertheless, continuous feedback and learner modelling are widely recognized as essential components of AI-driven educational robotics. Together with perception and adaptive decision making, they complete the adaptive learning cycle that enables educational robots to provide personalized, responsive, and learner-centred educational experiences.

6. Benefits and Educational Impact

The integration of AI into ER has significantly enhanced the ability of educational systems to deliver personalized, engaging, inclusive, and data-driven learning experiences. By combining adaptive learning, learner modelling, and intelligent interaction, AI-powered educational robots can support both learners and educators while improving overall educational effectiveness [42].

One of the most significant benefits of AI-driven educational robotics is the ability to provide personalized learning experiences. Through technologies such as Machine

Learning, Natural Language Processing, affective computing, and learning analytics, educational robots can continuously monitor learner progress and adapt instructional content, feedback, and learning pathways according to individual needs [42]. By generating dynamic learner profiles and providing real-time support, these systems promote improved knowledge retention, self-regulated learning, and academic confidence. Such adaptive capabilities represent a shift from traditional one-size-fits-all instruction toward learner-centred educational approaches [43].

Educational robots foster active participation and motivation by creating interactive and socially engaging learning environments. Through adaptive feedback, gamification, conversational interaction, and embodied learning experiences, robots encourage sustained learner attention and participation [9]. AI-based monitoring of behavioural indicators such as facial expressions, gaze direction, and engagement patterns further enables instructional adaptation in real time. Consequently, educational robotics contributes to increased learner motivation, creativity, collaboration, and overall engagement in the learning process [42].

AI-driven educational robotics also supports inclusive and accessible education by accommodating diverse learner needs. Through multimodal communication and adaptive instructional support, educational robots can assist learners with disabilities, language barriers, and varying cognitive abilities. These applications align with the goals of equitable and inclusive education advocated by the United Nations Sustainable Development Goal 4 (SDG 4) [44]. Furthermore, remote and telepresence technologies expand educational opportunities for learners in underserved or geographically isolated settings, helping reduce barriers to learning.

In addition to supporting learners, AI-powered educational robots can enhance teaching effectiveness by automating routine tasks such as assessment, progress monitoring, and classroom management. Advanced analytics provide educators with valuable insights into learner performance and engagement, facilitating data-driven instructional decisions. Rather than replacing teachers, educational robots function as intelligent assistants that complement human expertise and support more personalized and responsive learning environments [45].

The literature indicates that AI-driven educational robotics can improve personalization, engagement, accessibility, and instructional effectiveness. However, their educational impact ultimately depends on factors such as pedagogical design, teacher involvement, technological infrastructure, and implementation context.

7. Challenges, Ethical Considerations, and Future Research Directions

Despite the growing potential of AI-driven Educational Robotics in adaptive learning, several technical, ethical, and practical challenges remain. One of the most significant concerns is data privacy and child protection. Educational robots continuously collect behavioural, cognitive, and biometric data to personalize learning experiences, raising concerns regarding surveillance, unauthorized access, and misuse of sensitive information. These challenges are amplified in smart learning environments that employ cameras, sensors, and Internet of Things (IoT) devices for continuous monitoring. Ensuring compliance with privacy regulations and adopting privacy-by-design principles, transparent consent mechanisms, and secure data management practices are therefore essential [46].

Another critical issue is algorithmic bias and fairness. Since AI models are trained on historical data, they may inherit and reproduce existing social, cultural, or demographic biases, leading to unequal educational outcomes. Biases in emotion-recognition, facial-analysis, and adaptive learning systems may disproportionately affect learners from underrepresented groups. Addressing these concerns requires fairness-aware algorithms, diverse datasets, explainable AI techniques, and continuous human oversight to ensure equitable and inclusive educational practices [47].

Practical challenges related to cost, scalability, and accessibility also limit widespread adoption. The implementation of AI-enabled educational robotics often requires substantial investment in hardware, software, connectivity, and teacher training, which may not be available in resource-constrained educational settings [48]. Furthermore, excessive dependence on AI systems may reduce opportunities for social interaction, critical thinking, and independent problem-solving if not carefully balanced with human guidance. Consequently, educational robots should be viewed as tools that complement rather than replace educators. Effective teacher–robot collaboration remains essential to preserve human empathy, contextual understanding, and pedagogical judgment within technology-enhanced learning environments [46].

Future research is expected to focus on the integration of generative AI, multimodal interaction, lifelong learning systems, and immersive educational technologies. Large Language Models (LLMs) and generative AI can enable educational robots to provide personalized dialogue, adaptive tutoring, and dynamically generated learning resources. Similarly, multimodal AI systems that combine speech, gesture, gaze, and emotion recognition can facilitate more natural and human-like interactions while supporting diverse learner needs. Advances in reinforcement learning and online learning algorithms may also enable the development of self-improving educational robots capable of continuously adapting their instructional strategies over time [49].

Another promising direction is the integration of educational robotics with Augmented Reality (AR), Virtual Reality (VR), and Extended Reality (XR) environments. Such technologies can create immersive and interactive learning experiences in which robotic tutors provide real-time guidance and feedback within virtual learning spaces [50]. Together, these developments are expected to transform educational robots from programmable instructional tools into intelligent, adaptive, and lifelong learning companions. However, their successful implementation will depend on maintaining transparency, fairness, accessibility, and strong human oversight to ensure that technological innovation remains aligned with educational goals and societal values.

8. CONCLUSION

The convergence of AI and Educational Robotics is transforming adaptive learning by enabling personalized, interactive, and learner-centred educational experiences. This review examined the theoretical foundations of adaptive learning, the evolution of educational robotics, key AI technologies, architectural frameworks, educational impacts, and emerging research directions. The findings indicate that AI-driven educational robots can enhance personalization, learner engagement, accessibility, and instructional effectiveness through intelligent learner modelling, adaptive decision-making, and continuous feedback mechanisms. Technologies such as Machine Learning, Natural Language Processing, Computer Vision, and Reinforcement Learning have significantly expanded the capabilities of educational robots, enabling more responsive and adaptive learning environments. However, challenges related to data privacy, algorithmic bias, scalability, accessibility, and teacher–robot collaboration remain important considerations. Future advances in generative AI, multimodal interaction, lifelong learning systems, and immersive technologies are expected to further strengthen the role of educational robotics in education. Overall, AI-driven educational robotics represents a promising pathway toward more adaptive, inclusive, and effective learning ecosystems.

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