ADVANCE SOCIAL SCIENCE ARCHIVE JOURNAL
Available Online: https://assajournal.com
Vol. 05 No. 01. Jan-March 2026.Page#.103-131
Print ISSN: 3006-2497 Online ISSN: 3006-2500
Platform & Workflow by: Open Journal Systems
https://doi.org/10.5281/zenodo.18270365

The Future of Learning with AI: A Systematic Review on Transforming Student Education and Competencies

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Abstract
Artificial Intelligence in Education (AIED) has evolved into a substantial research field, generating a diverse body of literature with varied perspectives and applications. This review synthesizes empirical studies published between 2014 and 2024, examining AIED's integration across secondary and higher education with a focus on pedagogical strategies and tools, ethical considerations, institutional collaboration, and the application of machine learning models in teaching, learning, and assessment. An initial mapping of 4,076 research articles, refined through an in-depth analysis of 62 selected studies, provides a robust conceptual framework of the current knowledge landscape. The findings highlight AIED's transformative role in secondary and higher education by enhancing pedagogy, addressing ethical challenges, fostering institutional collaboration, and leveraging machine learning applications. These insights provide strategic direction for teachers, administrators, and policymakers in shaping effective, ethical, and inclusive integration of AIED in education. Future research should emphasize enhancing explainable AI, mitigating ethical risks, and evaluating AI tools in diverse real-world classroom contexts.

Keywords: *Artificial Intelligence in Education, Machine Learning Models, Ethical Challenge, pedagogical strategies, Explainable AI, Secondary and Higher Education*

Introduction
We are currently inhaling simulation of human intelligence or AI, where society can easily experience AI anywhere and anytime, as AI as a transformative technology is a set of

recommendations indistinguishable across many sectors such as the educational institutions and economics of information technology [1]. In his day to day life, virtually everybody has to make hundreds of choices a day. The premature progress in AI, mostly in machine learning and natural language processing (NLP), have assisted the construction of intelligent frameworks that are capable of executing tasks that previously demanded human intelligence[2]. In education, AI has a potential to customize learning experiences, systematize administrative processes, and increase research endeavors. Moreover, AI is renovating the IT industry by presenting new professional models and redesigning the competitive environment [3]. Recently, the integration of AI in education has garnered significant impression in AI teaching and learning (AITL) process. Over the past two decades with various applications like adaptive learning, Chabot's for student support and AI-driven research tools are frequently used. Before 2021, AITL process mainly focused on computer science education at the university level. Teaching AI wasn't widespread in K-12 classrooms back then because there weren't many tools exist that were suitable for low class's students and could effectively support their learning [4]. Computer science education has long explored how to teach students about artificial intelligence (AI) in universities, topics like robotics, software design, building models, and working with data structures. Learning and teaching for AI can be found in the 1970s when first LOGO encoding and Turtle robot was familiarized to young learners but such programing tools are mostly focus on computational philosophy or programming concepts instead of AI learning [5]. In 1995, the book "Artificial Intelligence: A Modern Approach" by Russell and Norvig became a key textbook for university level students learning about AI and its covered how AI can tenacity problems, reason, learn, make decisions, interconnect, perceive, and act. At that time, AI wasn't a major part of K-12 education because there were no suitable tools or teaching methods to help younger students learn about AI [6].

Recently, there has been growing interest in teaching AI to K-12 students and non-computer science university students, thanks to user-friendly tools like Teachable Machine, Tensor Flow Playground and AI for Ocean on Code.org. Such platforms allow students to create machine learning models without needing a background in computer science. The "five big ideas" framework was introduced to outline which AI concepts should be taught to students at various grade levels [7]. These ideas are: how AI perceives the world, how it represents and reasons about information, how it learns, how it interacts naturally with people, and the influence of AI on society. These ideas help to make AI education easier to understand and use. Also guiding educators, researchers, and government organizations in creating effective strategies and programs to ensure learners gain the necessary AI knowledge, skills, and attitudes. In today's development, we are going quickly towards modernization or automation in each and every domain of AI, and the education sector is also not untouched from this evolution.

Table 1 reveals the comparison between older education learning systems with new AI solutions and figure 1 shows the effect of AI factors and machine learning to improve education. Recent research climaxes the multilayered impact of AI in education. Educationalists report about saving up to six or more hours per week and improved student engagement through AI-supported lesson design and grading [8] .Systematic reviews of intelligent tutoring systems (ITS) have inveterate that these AI-driven tools like Tutor Copilot, Google Gemini and ChatGPT (OpenAI) lead to measurable academic improvements among K–12 students as well as those in higher education and other academic departments [9].

Table 1

Comparison of Traditional Learning Systems and AI Solutions[10]

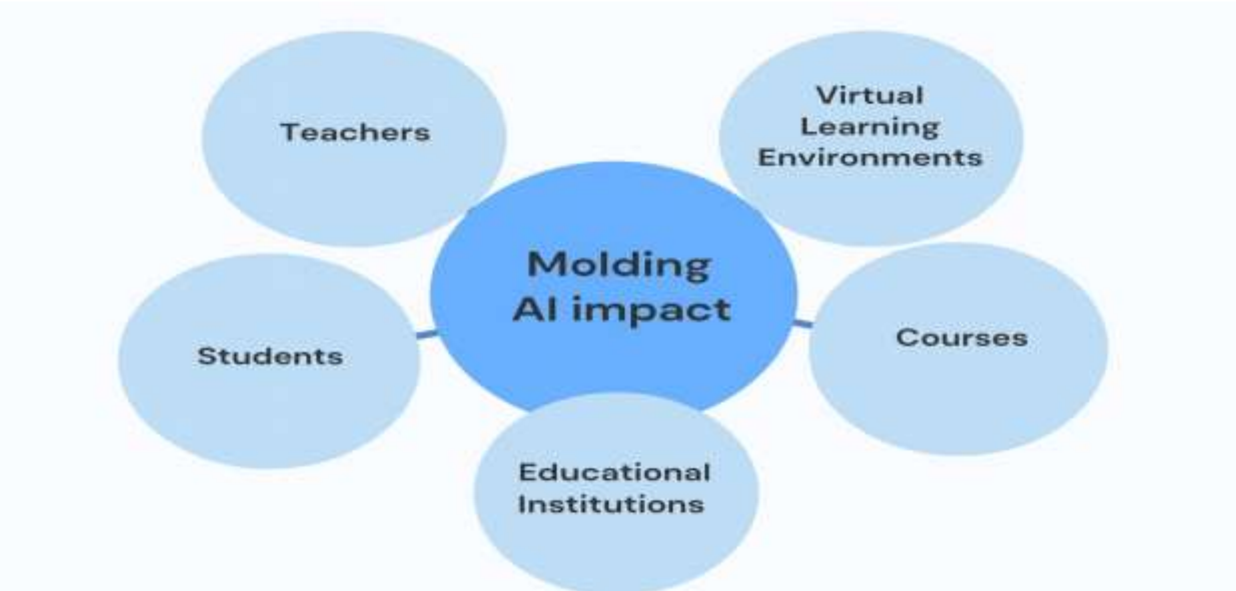
Older Learning System	
Standardized curricula do not cater to individual needs	Personalized learning
Limited one-to-one time available for students	Personal virtual tutor
Large classes in K–12 schools mean children's questions often go unanswered	Virtual classroom assistants
Personalized communication is almost impossible due to scale	Chatbots can answer administrative questions on the fly from parents, staff, and students
Selecting the best students for a large application pool	AI can shortlist candidates based on multiple data points
Increasing dropout rate at schools and universities	AI sentiment analysis for early intervention

Another useful approach in education is hybrid human AI approaches that refer to instructional models where AI works alongside human teachers to enhance the learning experience. Instead of replacing tutors, AI systems support them by providing real-time data, adaptive content, and custom-made feedback based on each student's performance. Tutor CoPilot is notable model, which supports teachers by endorsing next-step actions during tutoring sessions. This collaborative setup empowers more efficient and personalized instruction, particularly in classrooms with limited resources or large student number[11].In 2025, the background of AI in education has quickly evolved, leading a new wave of AI tools and hybrid learning models designed to boost teaching and learning across various levels. Among the most famous is Kira Learning, an AI teaching and learning assistant platform designed by Andrew Ng's team, which supports educationalists by automating lesson planning, grading, and real-time analysis of student progress is using Socratic teaching methods. Also, Khanmigo, created by Khan Academy in teamwork with Microsoft, offers personalized tutoring, writing feedback, and analytics for teachers, making it one of the most impactful simulated tutors in current use [12]. For newer learners, PinwheelGPT offers a safe AI one-to-one environment for children aged 7–12, with built-in content filtering and paternal controls to promote creative learning without exposure to dangerous material [13]. VTutor and Tutor loop AI is hybrid learning tools combine human mistake with AI-based aristocrat monitoring and session feedback, empowering tutors to simultaneously manage and support several students through real-time interaction indications [14]. NeuroChat go a step further by incorporating EEG-based feedback to adjust content pacing and complexity according to the learner's cognitive engagement. Meanwhile, MindScratch and LessonForge assist learners in programming and work-based training through code scaffolding on context and content based on domain manuals. There are also other models such as SocratiQ that are reforming STEM education through the process of simulating Socratic discourse and enhancing critical thinking via question-based learning. All these enhancements represent a significant movement toward AI-enhanced personalization, cognitive interaction and teacher enhancement in both K12 and higher education schools [15].

The education sector is now using technology to improve teaching and learning. This includes online tutorials, smart boards, intelligent tutoring systems, Chabot's, and even robots in classrooms. These tools help teachers teach more effectively and make learning easier for students [16]. The rapid growth of AI expertise is standardizing the execution and utilization of AI in education. The knowledge transfer based on problem-solving is emerging into the creative convergence type. Individualized education according to the AI era is substituting with the collective-type public education which was founded on the age of industrialization. The persistence, satisfaction and approaches to education are taking a fast-paced shape. AI is accelerate the transition by transforming the ways we educate and learn, personalizing education, making it more accessible and data-driven[17].

Figure 1

Impact Factors of AI and Machine Learning to Improve Education



Note. The diagram illustrates the multidimensional influence of the AIED. AI does not only influence the characters of teachers and students, it changes learning institutions, courses, and virtual learning environments, thus shaping the entire educational landscape.

The concept of AI in education became known in 2016, but in 2021, it reached a significant traction, as the number of related publications has grown by orders of magnitude (23 publications in that year, versus 3 to 5 annually before 2016). It indicates that 2021 was a crucial year in education research in AI [18]. We immediately need a detailed study of how AI is empathetic education. With the increasing number of AIED research papers, it's important to systematically explore these impacts. Current studies often emphasis on specific areas like higher or special education, but a broad overview of AI's effects on all educational contexts is still missing. This review addresses key research questions that cover: 1) How teaching and learning AI has surprisingly become popular in both secondary or Inter level and computer science education or non-computer science university education. 2) How Pedagogical approaches and training tools used in the selected studies and gain popularity. 3) What ethical trepidations have emerged regarding the use of AI tools in education, and in what way are they being addressed? 4) How can AI play its role for foster collaborative research opportunities among institutions of higher learning or Postgraduate institutions, and open online courses. 5) What are the most frequently machine learning (ML) models used in education, and in what way they contribute to student outcomes?

To comprehend the development of AIED study, this research has comprised both peer-reviewed scholarly articles and also some conference papers regarding how to teach and learn AI in education.

Methodology

The current study worked diligently to sightsee how AI is transforming learning and teaching impact on education at both secondary and intermediate levels by enabling intelligent tutoring systems, personalized learning paths, and adaptive assessment tools that cater to diverse learning abilities, thereby improving student engagement and academic performance. The purpose of this systematic literature review (SLR) is to sum up the knowledge related to impact of AI in education and know the status of research associated to a particular domain or a specific phenomenon. A structured process proposed by the widely used review methodology called Preferred Reporting Items for Systematic Reviews and Meta Analyses (PRISMA)[19]. The review approach define the study's purpose along with precise research questions, articulating a procedure, a widespread literature search, prepared screening process, mining pertinent data, and synthesizing the findings. The sections below completely mention how each of these steps was carried out for this study.

Research Questions and Motivation

To clearly define the scope and objectives of this SLR, the Population, Intervention, Comparison, Outcomes, and Context (PICOC) framework was adopted. This helped ensure a systematic approach to formulating research questions and minimized the risk of selection bias. The population (P) targeted in this review includes educators, students, and institutions across both secondary/intermediate schools and higher education, encompassing computer science and non-computer science disciplines. The intervention (I) focuses on the use of Artificial Intelligence (AI) and Machine Learning (ML) tools, platforms, and strategies that support teaching, learning, collaboration, and educational analysis. For comparison (C), the review contrasts AI-supported educational methods with traditional, non-AI-based practices and pedagogical approaches. The expected outcomes (O) include improvements in learning results, teaching effectiveness, collaborative research capacity, ethical preparedness, and model adoption. The context (C) spans global formal education settings including secondary schools, universities, and open online platforms covering publications between 2014 and 2024. The motivation of this research questions are articulated in Table 2.

Search Strategy

We retrieved a variety of prominent databases and digital sources to search the significant literature. Particularly, PubMed, IEEE Xplore, ACM, Scopus and Science Direct to extract relevant data.

Table 2

Research Questions and their Motivations

Research Question	Motivation
How has AI education gained popularity across secondary and university levels in both CS and non-CS fields?	To understand AI's rapid curriculum integration across education systems and its acceptance in both technical and non-technical domains.
What pedagogical approaches and AI-based training tools are being used, and how have they gained popularity?	To identify shifts in instructional design and tools that enhances learner engagement and instructional efficiency.

Research Question	Motivation
What ethical concerns have emerged regarding the use of AI tools in education, and how are they being addressed?	To examine institutional and policy-level responses to data privacy, bias, and other ethical concerns arising from AI in education.
How can AI foster collaborative research and teaching among institutions, especially in higher education and open online courses?	To explore AI's role in enabling collaborative teaching and research across institutional and national boundaries.
What machine learning (ML) models are most frequently used in education, and how do they contribute to student outcomes.	To highlight the impact of widely-used ML models on prediction, personalization, and performance improvements in education.

This research used advanced search option to limit our search consequences to papers published between 2014 and 2024, ensuring that our search was focused and up to date [20]. Also this research used a keen search strategy along with a number of search terms and operators to achieve desired results. The purposed scheme used a combination of key terms such as (AI-based education) OR (artificial intelligence in education) AND (AI factors influencing on students' education)) AND (impact of Teaching AI on K-12 education) AND (influence of AI on computer science education or non-computer science university education) OR (Pedagogical approaches and teaching tools used in e-learning) OR (open online courses or Machine learning (ML) models in student outcomes). The combinations of search term, along with their possible dissimilarities were applied to search within the keywords, papers, titles, and abstracts. This examination strategy was created with the intention to identify and consider a wide- range of experiential work relating to the use of AI in the teaching and learning of education scenario. The following inclusion/exclusion criteria were implemented: (1) only articles, excluding the so-called grey literature; (2) whose language was English; (3) published between 2014 and 2024; (4) belonged to the area of "Educational research or Education in AI" in the case of WOS and Science Direct, and the research areas "social sciences, art and humanities" in case of Scopus, PubMed, also "Computer science and technology-focused education" in the case of ACM.

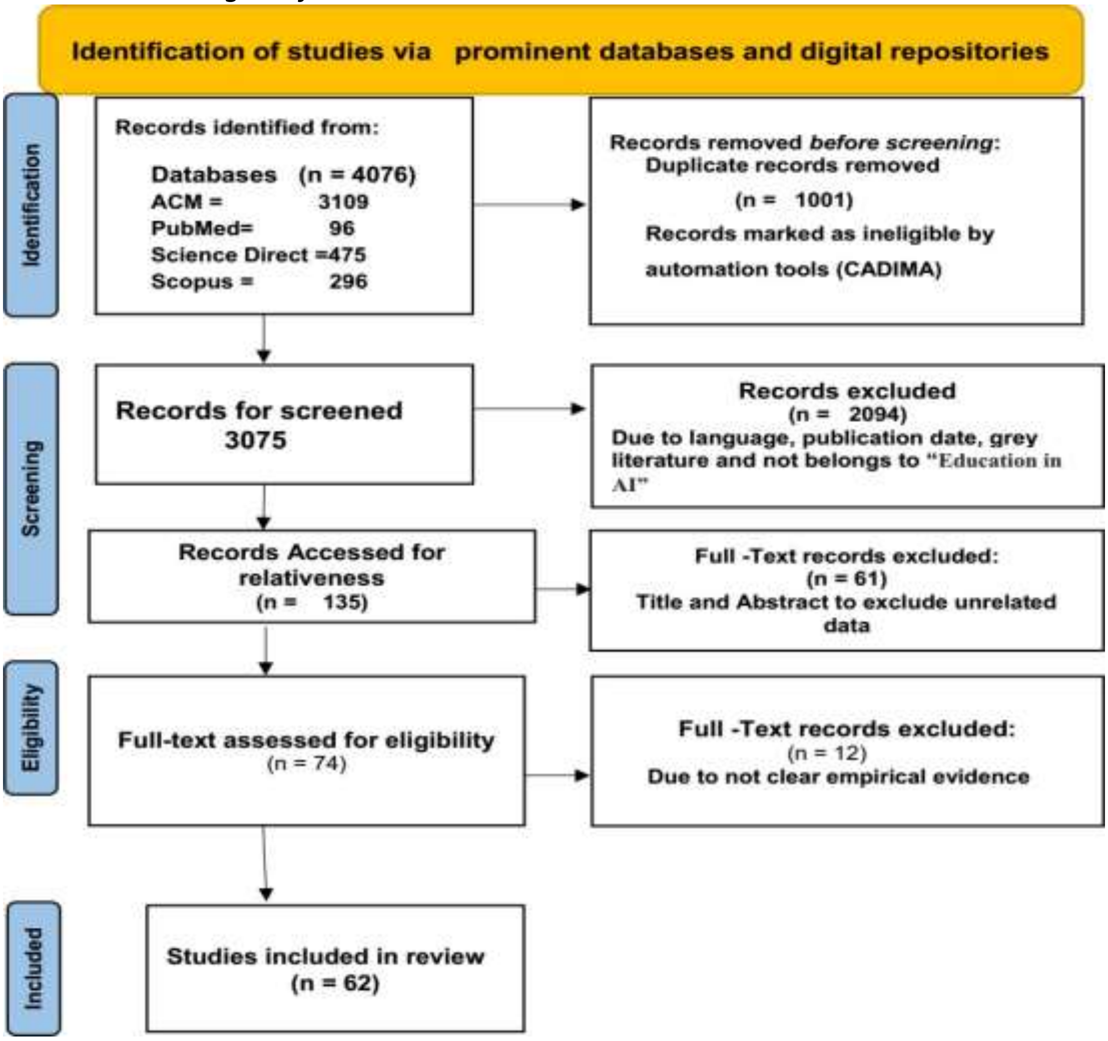
Screening Process

The search was initiated in November 2024, and the very first step 4076 records identified initially. The study obtained 135 articles after removing duplicates, verifying article dates and titles, and at the end examining abstracts to determine whether they satisfied the requirements for this study.61 research articles were then excluded since they didn't go deeply enough into online education or AI related education instruction. We carefully went through the 74 articles that were remaining. Before delving into them, we ensured they associated with our criteria and effectively addressed our research questions. 12 articles were also filter from the pool of these 74 articles because they fall shorts of convincing empirical support for the use of AI in current education. This process brings about final dataset of 62 articles that were included in the SLR and display in figure 2 as PRISMA flow diagram The articles incorporated in our SLR are summarized in Table 3, and their thematic distribution is illustrated in Figure 3.

This chart highlights the most frequently studied domains within the selected literature. General Education emerged as the most dominant focus, followed by Teacher Education, Science Education, and MOOCs. In addition, specialized areas such as AI in E-learning and personalized Learning were also represented, underscoring the expanding scope and interdisciplinary relevance of AI applications across diverse educational contexts.

Figure 2

PRISMA Flow Diagram for the Search and Selection Process



Note. This PRISMA diagram illustrates the systematic review process following PRISMA 2020 guidelines [21].

Table 3

Articles Included in the Systematic Review (2014–2024)

PID	Authors Name	Field of Study	Methodology
P1	Almasri, F. (2024)	Science Education	Qualitative
P2	Jay, L. P. (2024)	Teacher Education	Qualitative
P3	Di Pietro, G., et al. (2024)	Digital Education	Quantitative

PID	Authors Name	Field of Study	Methodology
P4	Fang, G., et al. (2024)	Education	Mixed
P5	Ottogalli, M. E., et al. (2024)	Elementary Education	Qualitative
P6	Fungra, C., et al. (2021)	Education	Qualitative
P7	Yin, H., et al. (2024)	Teacher Perception	Quantitative
P8	Huang, L., et al. (2024)	Teacher Education	Qualitative
P9	Demir, M., et al. (2023)	Education	Qualitative
P10	Okoye, K., et al. (2023)	Education	Qualitative
P11	Yu, W., et al. (2022)	Learning Tools	Qualitative
P12	Aouine, A., et al. (2014)	Education	Mixed
P13	Skalka, J., et al. (2020)	Modern Applications	Qualitative
P14	Dhandapani, A., et al. (2023)	ML in Learning	Qualitative
P15	Sie, R. L. L., et al. (2018)	Online Learning	Qualitative
P16	Ng, R., et al. (2024)	Primary School Education	Qualitative
P17	Ahmad, K., et al. (2024)	Data-driven AI	Mixed
P18	Balaa, Z. E. L., et al. (2016)	Education	Qualitative
P19	Wang, X., et al. (2024)	Education	Qualitative
P20	Sanchez, B., et al. (2021)	Engineering Education	Qualitative
P21	Mendoza-Chan, J., et al. (2024)	Digital Skills	Quantitative
P22	Zhang, W., et al. (2018)	E-learning Assessment	Qualitative
P23	Son, T., et al. (2024)	Teacher Education	Qualitative
P24	Almasri, F., et al. (2024)	Science Education	Qualitative
P25	Wei, X., et al. (2024)	MOOCs	Mixed
P26	Sushchenko, O., & Otenko, V. (2022)	Distance Learning	Qualitative
P27	Shi, Y., et al. (2015)	Interactive Whiteboard Learning	Quantitative
P28	Børte, K., et al. (2024)	Education	Quantitative
P29	Kedrova, G., & Potemkin, S. (2015)	Education	Qualitative
P30	Zhang, S., et al. (2024)	Education	Qualitative
P31	Chapke, M. P. P., & Raut, A. B. (2023)	Online Education	Qualitative
P32	Liu, Z., & Tang, Q. (2024)	MOOCs	Qualitative
P33	Pozo-Rico, T., et al. (2024)	Education	Qualitative
P34	Shafique, R., et al. (2023)	AI in Education	Qualitative
P35	Chapke, P. P., & Raut, A. B. (2024)	ML-based Education	Quantitative
P36	Schulz, R., et al. (2014)	E-learning	Qualitative
P37	Chiu, K., et al. (2023)	AI in Education	Qualitative
P38	Claro, M., et al. (2024)	Teacher Competency	Qualitative
P39	Kang, H., et al. (2024)	K-12 Education	Qualitative

PID	Authors Name	Field of Study	Methodology
P40	McGarr, O. (2024)	Teacher Education	Qualitative
P41	Marco, N., et al. (2024)	Teacher Education	Qualitative
P42	Moylan, R., et al. (2024)	AI & Teaching	Qualitative
P43	Chiu, T. K. F. (2023)	Generative AI	Qualitative
P44	Ouatia, A., et al. (2015)	Higher Education	Qualitative
P45	Salem, A.-B. M. (2015)	Education	Qualitative
P46	Shete, M., et al. (2022)	ML in Education	Qualitative
P47	Tang, K.-Y., et al. (2023)	AI in E-learning	Qualitative
P48	Kevin, A., et al. (2024)	Personalized Learning	Qualitative
P49	Zhang, S., et al. (2024)	Pedagogical Agents	Mixed
P50	Zainuddin, N., et al. (2020)	Education	Mixed
P51	Balaa, Z. E. L., et al. (2016)	Education	Qualitative
P52	Yu, W., et al. (2024)	Education	Qualitative
P53	Yin, H., et al. (2014)	Distance Learning Tools	Qualitative
P54	Sushchenko, O., et al. (2022)	Scientific e-Libraries	Qualitative
P55	Kedrova, G., & Potemkin, S. (2015)	Education	Qualitative
P56	Shete, M., et al. (2022)	Education	Qualitative
P57	Salem, A.-B. M. (2015)	Education	Qualitative
P58	Schulz, R., et al. (2014)	Education	Qualitative
P59	Chapke, P. P., et al. (2014)	Education	Qualitative
P60	Shafique, R., et al. (2023)	Education	Qualitative
P61	Chapke, M. P. P., et al. (2023)	Education	Qualitative
P62	Ferrarelli, A., & Iocchi, L. (2022)	Education	Qualitative

Complementing this, Figure 4 illustrates the publication trends of the 62 reviewed studies over time. A sharp increase in research activity is evident in 2024, which accounts for 44% of the total studies, signaling a recent and intense academic interest in AI-driven educational innovation.

The years 2023, 2022, and 2021 also saw notable contributions, reflecting the momentum AI has gained in teaching and learning. In contrast, earlier years such as 2014 and 2015 had comparatively fewer publications, suggesting that the role of AI in education has significantly intensified over the past five years.

Figure 3

Most Frequently Studied Domains within the Selected Literature

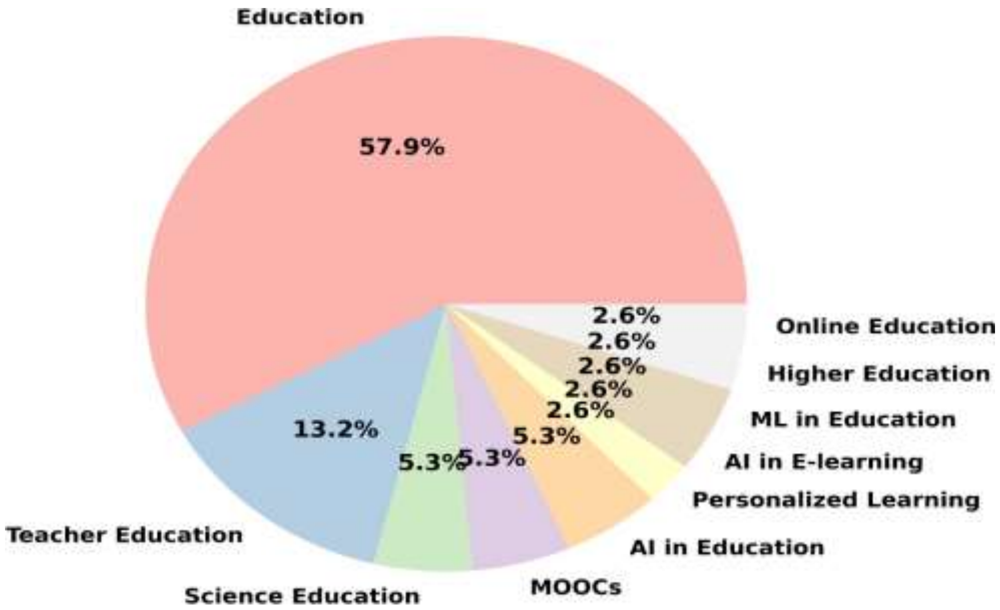
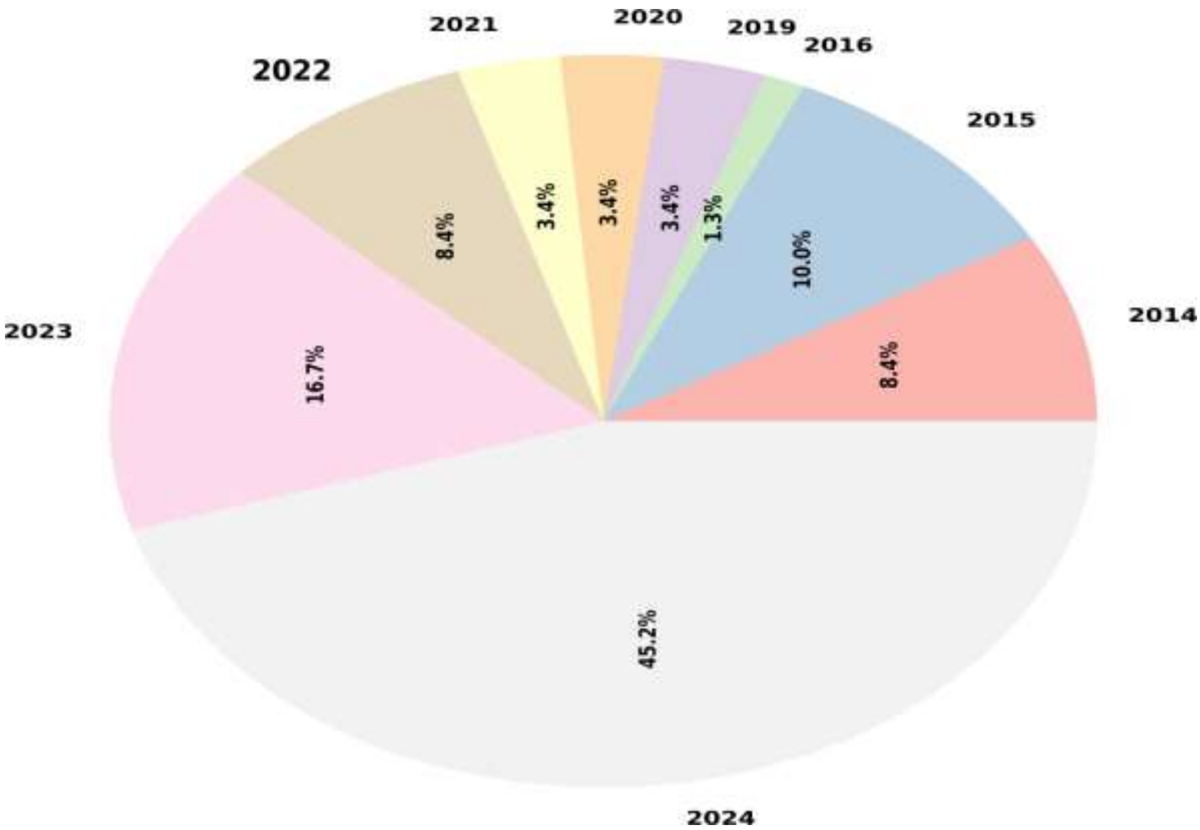


Figure 4

Publication Trends of the 62 Reviewed Studies over a Time



Selection Criteria

For the practical papers to be included in this review paper, they must fulfill the following requirements. The study's goals were to: (a) quantify the effect of AI on education, or one of its components, on online education; (b) focus on secondary and intermediate education; (c) have a dependent variable that was connected to academic performance in computer science and non-computer science education; and (d) pupils have to be included in the sample. The Table 4 presented the inclusion and exclusion criteria. The usage of AI in education is becoming more and more popular since there are a lot of new and exploding possibilities in this field. Table 5 demonstrates the trends of rising popularity in AI base education from 2014 to 2024 and depicted in figure 5.

Table 4

Inclusion and Exclusion Criteria

Inclusion	Exclusion
Research must base on empirical study.	The articles do not covered Artificial in education.
The papers present results of the application of AI in education to improve performance matric.	Thesis, editorial writings, meeting abstract, book chapter, book, and biographical items are left out from SLR.
This SLR included conference proceedings, and journal articles written in English language.	Papers mentioning “artificial intelligence” but focusing on unrelated subject areas are excluded.
Only articles that meet the quantity, qualitative and mix method content analysis criteria are included.	Design-based investigations, conceptual/theoretical frameworks, and abstract-only papers are excluded.

Table 5

AI in Education Key Trends

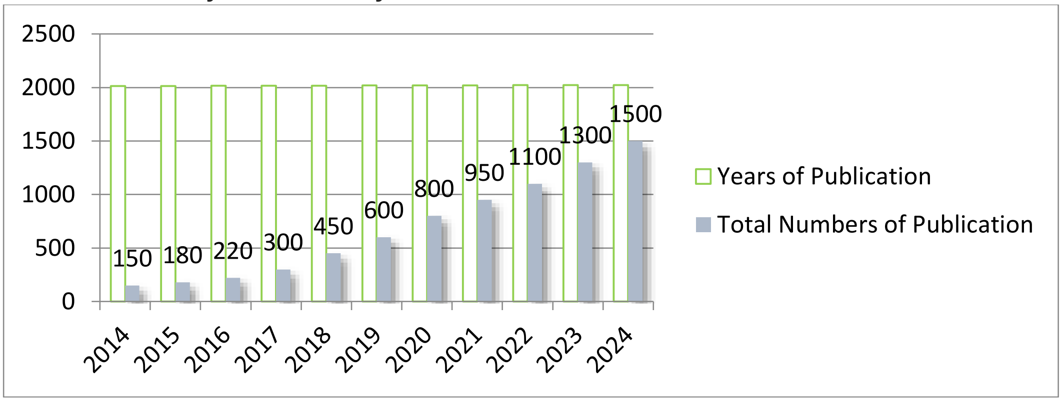
Years	Total Numbers of Publication	Key areas
2014	150	First exploration of AI's possible potential in education. Topics include adaptive learning (AL) and intelligent tutoring systems (ITS).
2015	180	Significant growth with most focuses on Massive Open Online Course (MOOCs) and personalized learning systems.
2016	220	Research trends on machine learning applications in education.
2017	300	Cooperation between academia and educational technology establishments accelerates.
2018	450	Emphasis on AI ethics, student commitment, and ease of access in education.
2019	600	AI base supported technologies assessments and response systems gain popularity.

Years	Total Numbers of Publication	Key areas
2020	800	Gush due to COVID-19 and move to online learning platforms.
2021	950	Broader applications (BP) of AI in personalized education and proficiency development.
2022	1100	Rising motivation on equity and AI-driven educational tools.
2023	1300	Advanced AI prototypes like ChatGPT, quillbot etc. explored for teaching and learning.
2024	1500	Projected increase in in this year because of the AI-driven curriculums and hybrid education models researched.

Note. This table summarizes the primary trends in AI adoption in education as identified in the systematic review. Its highlights both the increasing volume of studies and the evolution of research themes, from early exploration of adaptive learning and tutoring systems to recent focus on advanced AI models, ethics, and hybrid educational models.

Figure 5

Total Numbers of Publication from Years 2014 to 2024



Note. This figure shows the annual growth of publications on artificial intelligence in education between 2014 and 2024. The trend indicates a steady increase in research output, with a sharp rise during 2020 due to COVID-19 and a continued surge as AI-driven curricula and advanced educational tools gained popularity in subsequent years.

Coding and Analysis

This research used both quantitative and qualitative content analysis to summarize the results of the empirical study. A small randomly chosen set sample of 20 carefully nominated articles was independently coded by several raters. This process was conducted to ensure inter-rater reliability in evaluating the quality of the article coding techniques. The computed reliability level was higher than 90%, indicating a high level of agreement between the various coding categories. We carried out an extensive analysis of the studies from a number of angles. First, we examined the data set's attributes, such as the nation in which the research was carried out, the paper name, the subject matter, and the educational attainment.

Findings

In this extensive SLR, we thoroughly assessed sixty two (62) empirical studies that addressing the application of AI in education. A number of research approaches, such as mixed, qualitative, and quantitative approaches were used in these studies. Analyzing the publication years of the nominated studies revealed a distribution across the 10-year timeframe of the review (2014–2024). Forty one (41) papers published in 2024, led the way signifying researchers ‘strong interest in the most recent research on the application of AIED. This was followed by (27) studies in 2023, nine (09) studies in 2022, and eight (08) studies in year 2021.

The current study's evaluation procedure involves combining the results associated to five different research issues, each of which is covered in detail in the following section.

Results

This section presents the findings of the SLR across five major research questions (RQs), each corresponding to key areas of interest in the intersection between Artificial Intelligence (AI) and education. These findings are synthesized from 62 empirical studies published between 2014 and 2024, offering insights into current trends, tools, pedagogical approaches, and challenges in AI-enhanced education.

RQ1: How has teaching and learning AI gained popularity at the secondary/intermediate level and among non-computer science university students?

The review revealed a noticeable shift in AI education outreach from tertiary-level computer science curricula to more inclusive and early-stage interventions. In 62 reviewed studies, 38 highlighted initiatives introducing AI concepts to K–12 or non-computer science learners through user-friendly platforms such as Teachable Machine, AI for Oceans, and Scratch with ML extensions [22].The review indicates a growing trend in extending AI education beyond traditional university-level computer science programs. Several studies documented that, prior to 2020; AI education was mostly limited to technical domains, often focusing on data structures, robotics, and software design.

However, in recent years, educators have begun introducing AI concepts at earlier educational stages, including middle and high schools. This shift has been facilitated by accessible and interactive tools such as Teachable Machine, AI for Oceans, and TensorFlow Playground, which allow students to experiment with AI and machine learning models without requiring a strong programming background. Furthermore, the development of the "Five Big Ideas in AI" framework has provided structure to this emerging curriculum, helping educators teach key AI principles perception, representation, learning, interaction, and societal impact [23].These efforts have also extended into non-computer science university disciplines such as business, healthcare, and education, demonstrating that AI literacy is becoming an essential skill across diverse fields. The studies reviewed suggest that this democratization of AI education is fostering student curiosity, enhancing problem-solving skills, and preparing learners for future careers in AI-driven environments [24]

An essential finding of the review is the rise of accessible, no-code AI platforms designed to engage learners from non-technical backgrounds. As shown in Table 6, various tools have emerged to cater to different educational levels. For instance, platforms like Teachable Machine and AI for Oceans allow K–12 students to explore basic machine learning and AI concepts through interactive, visual activities [25],[26]. Similarly, TensorFlow Playground helps secondary and tertiary-level students visualize how neural networks operate, thereby building intuitive understanding before diving into complex mathematics or coding.

Table 6

AI Tools for Teaching and Learning ([27]

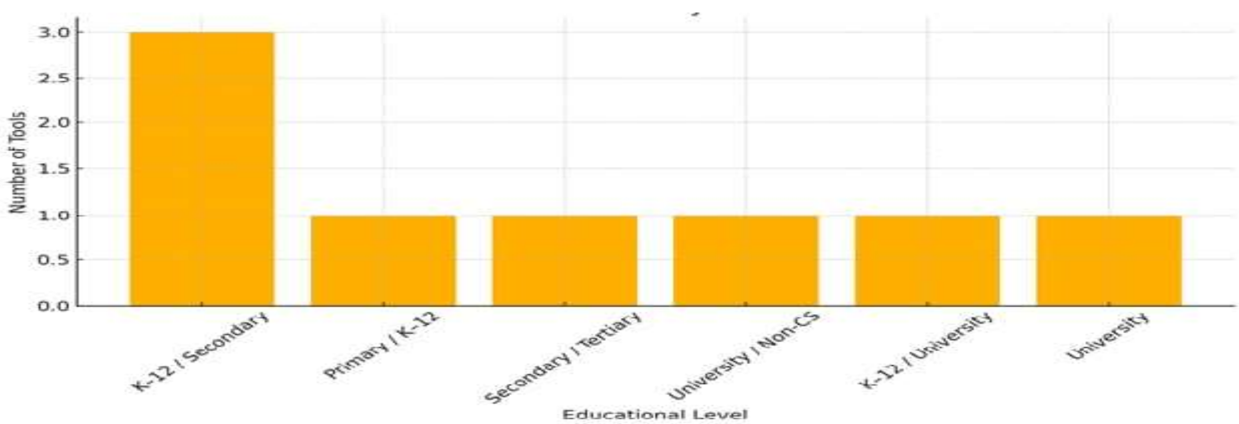
Tool/Platform	Target Level	Purpose
Teachable Machine	K–12 / Secondary	Build ML models without coding
AI for Oceans	Primary / K–12	Interactive AI concept exploration
TensorFlow Playground	Secondary / Tertiary	Visualize and experiment with neural networks
Scratch (with ML)	K–12 / Intro CS	Introduce ML via block-based programming
Kira Learning	University / Non-CS	Lesson planning and real-time student feedback
Khanmigo	K–12 / University	AI tutor for personalized and adaptive learning
Tutor CoPilot	University	Real-time AI-assisted tutoring support

These platforms are designed not only for computer science students but also for learners in subjects such as business, healthcare, and social studies. For example, Kira Learning and Khanmigo have been widely adopted by university programs outside of traditional STEM fields to assist instructors in delivering adaptive, real-time feedback, automating grading, and providing AI-assisted tutoring [28].Tools like Scratch with ML extensions also extend introductory AI education to younger students through gamified, block-based coding interfaces [29].

To further understand the distribution of these tools, Figure 6 presents a bar chart illustrating the number of platforms associated with each educational level. The data shows that the K–12 and secondary levels account for the highest number of AI tools, with three of the seven tools explicitly designed for these stages. In contrast, only one tool (Tutor CoPilot) exclusively targets university-level education, while a few others (e.g., Khanmigo) span both secondary and tertiary audiences. This visual evidence challenges the common assumption that AI tools are predominantly used in higher education.

Figure 6

Number of Platforms Associated with each Educational Level



While university-level tools exist and are impactful especially in automating administrative tasks and supporting non-CS learners the data clearly show a strong and growing movement to democratize AI education at younger stages [30].The presence of intuitive, low-barrier platforms has enabled educators to introduce AI not only to students pursuing computer science but also to those in non-technical fields who will eventually work in AI-influenced professions.

In conclusion, AI education is no longer confined to elite or technical disciplines. Instead, the review shows a broader pedagogical shift towards early, interdisciplinary, and inclusive AI learning, driven by purpose-built tools that align with cognitive levels and curriculum needs at both secondary and university levels. This change reflects a growing educational priority to prepare all learners not just computer science students for an AI-enabled future.

RQ2: What pedagogical approaches and AI-based training tools are gaining popularity in secondary and university-level education?

The reviewed studies report an increasing reliance on AI-based pedagogical tools that support adaptive, personalized, and efficient learning. Platforms like Khanmigo, Kira Learning, and Tutor CoPilot were commonly cited in 32 studies, for their ability to automate lesson planning, provide real-time analytics, and adapt instructional content to individual learning needs [31],[32].These tools are not replacing teachers but enhancing their capacity to deliver differentiated instruction, particularly in large or resource-constrained classrooms. A notable trend is the adoption of hybrid learning models where AI systems work collaboratively with human educators. For example, Tutor CoPilot offers intelligent suggestions during live teaching sessions, enabling instructors to respond more effectively to student needs [33].

In addition, AI-powered tutors such as SocratiQ are designed to simulate inquiry-based learning, promoting critical thinking through Socratic dialogue and personalized questioning [34]. This shift in pedagogy reflects a broader movement toward student-centered learning, where AI not only supports content delivery but also shapes how students engage, reflect, and participate in the learning process. Importantly, these tools are being integrated across disciplines, suggesting that AI is no longer confined to computer science education but is influencing general educational strategies [35].The Table 7 presents four widely referenced AI-driven educational platforms Khanmigo, Kira Learning, Tutor CoPilot, and SocratiQ along with their core functionalities and implementation contexts.

Table 7

AI Pedagogical Tools and their Use Cases [36]

AI Tool	Core Functionality	Use Case
Khanmigo	Personalized tutoring and writing feedback	K-12 and University learners across subjects
Kira Learning	Automated lesson planning and real-time analytics	Non-CS university students and instructors
Tutor CoPilot	AI-assisted real-time teaching support	Teacher augmentation in large classrooms
SocratiQ	Socratic dialogue and critical thinking	Promoting inquiry-based learning

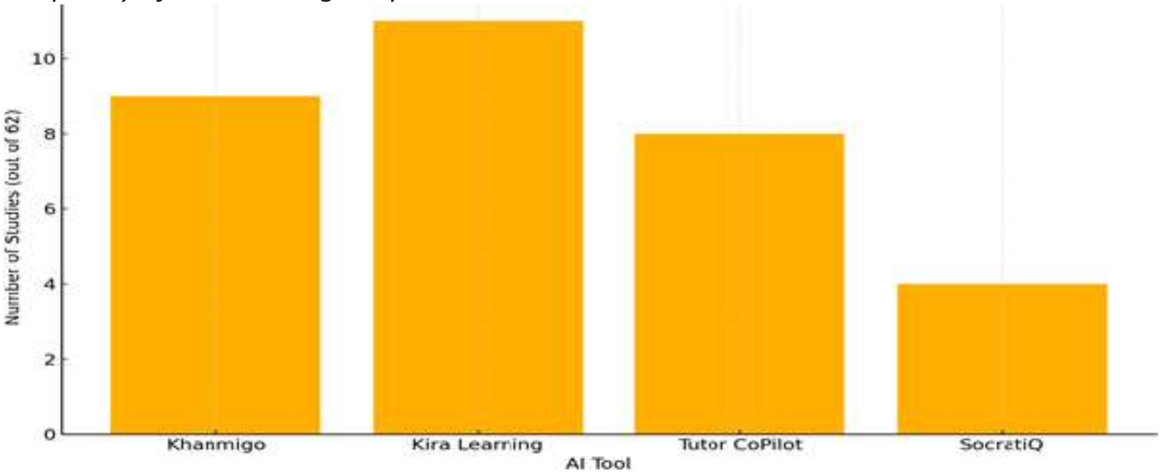
Note. This table highlights selected AI tools and their functionalities in education. The examples illustrate how AI supports diverse instructional practices, including tutoring, lesson planning, classroom augmentation, and inquiry-based learning.

These tools collectively illustrate how AI is being applied to personalize instruction, automate administrative tasks, and foster critical thinking across various educational settings. While Khanmigo and Kira Learning are frequently used in both K–12 and higher education, Tutor CoPilot and SocratiQ are more focused on teacher augmentation and inquiry-based learning, respectively. The range of tools and their interdisciplinary integration highlights the broader pedagogical shift toward student-centered, AI-enhanced instruction.

The Figure 7 shows the bar charts that articulated how often each AI tool was cited in the 62 empirical studies included in this review. Kira Learning was the most frequently mentioned, appearing in 11 studies, followed by Khanmigo (9), Tutor CoPilot (8), and SocratiQ (4). This frequency analysis supports the claim that these platforms are gaining traction in contemporary educational practice and research. It also reflects a growing interest in hybrid learning models, where AI technologies are used not to replace educators but to enhance their instructional capacity and improve learner outcomes.

Figure 7

Frequency of AI Tool Usage Reported in Studies



RQ3: What ethical concerns have emerged regarding the use of AI tools in education, and how are they being addressed?

A growing body of literature represented in 34 of the reviewed studies has raised important ethical concerns regarding the use of Artificial Intelligence (AI) tools in educational settings. These issues are connected to three main problems, namely, student data privacy and surveillance, algorithmic bias and equity, and excessive reliance on AI to make decisions[37].

To begin with, privacy of student data is now a significant concern, especially as AI handles and processes data in vast quantities of sensitive personal information, including learning behavior, performance indicators, and emotional indicators. These systems are in use continuously in some instances, which leads to concern of being watched and this would impact student autonomy and mental health. In an attempt to counter this, there are the introduction of differential privacy algorithms and secure profiling in 9 studies. They anonymize data and limit the chances of re identification, which means that institutions can retain functionality without interfering with the privacy of individual persons [38].Second, algorithmic bias in which AI models unintentionally reproduce or increase social inequities as they exist was an issue in both predictive, learning systems and individualized assessment tools. A number of studies that were reviewed highlighted that AI recommendations were sometimes tilted against students in marginalized or underrepresented backgrounds. Researchers and developers in select institutions responded to this by creating and developing them started integrating explainable and transparent AI models, which enabled students and others teachers to know the reason behind certain choices. These models promote accountability and reduce "black-box" risks by highlighting the feature contributions used in decision-making [39],[40].

Third, the issue of over-dependence on AI for pedagogical and administrative decisions such as grading, feedback, or even career counseling was flagged as a potential threat to human judgment and professional discretion. Six studies introduced an innovative response and integration of AI ethics education directly into the curriculum. These lessons covered foundational concepts like algorithmic bias, transparency, fairness, and accountability, empowering students to critically evaluate the tools they use [41].

Despite these emerging strategies, the review noted that ethical discourse around AI in education remains fragmented, especially in secondary education settings. In many countries, policy development lags behind practice, resulting in inconsistent implementation of safeguards. There is a clear need for more proactive, centralized regulation and teacher training programs that address the ethical implications of AI deployment [42].Table 8 summarizes key mitigation strategies such as differential privacy, Explainable AI, and ethics-focused curricula used to address ethical concerns in AI education, along with the number of studies implementing each.

Table 8

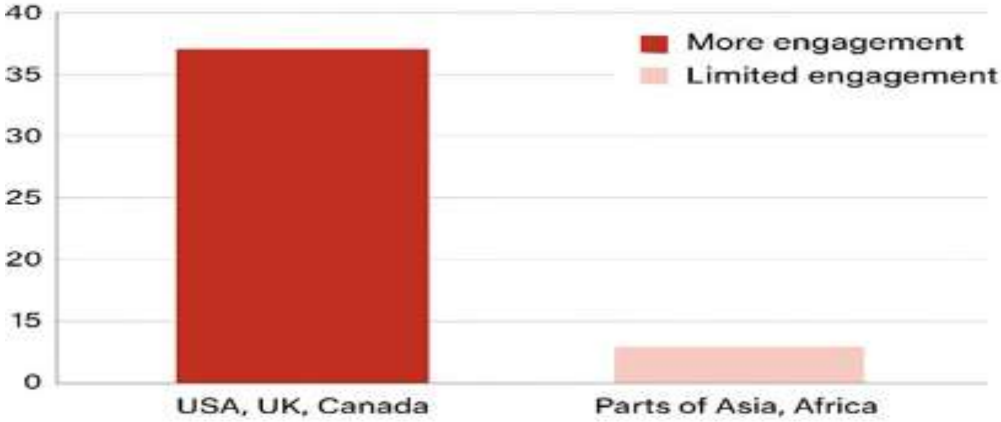
Summary of Ethical Mitigation Strategies [43]

Mitigation Strategy	Description	Studies Implemented
Differential Privacy Algorithms	Anonymizing student data to protect identity	9
Explainable AI Systems	Making model decisions interpretable to users	13
AI Ethics Lessons in Curriculum	Teaching students about bias, transparency, and accountability	6
Institutional Policies or Frameworks	Internal data handling, consent, and transparency policies	7

Figure 8 visualizes the global distribution of ethical discourse in AI education using charts of Countries such as the USA, UK, and Canada are marked higher levels of engagement in policy and research around AI ethics. In contrast, many parts of Asia and Africa appear in lighter tones, reflecting limited or emerging attention to these issues. This figure reinforces the geographic imbalance in ethical preparedness and calls for more global collaboration.

Figure 8

Map Global Distribution of Ethical Discourse in AI Education



***RQ4*: How can AI foster collaborative research and teaching among institutions, especially in higher education and open online courses?**

Based on the analysis of the 62 selected studies, AI is increasingly enabling collaborative teaching and research across institutions through shared platforms, intelligent systems, and distributed learning models. Approximately 21 studies reported the use of AI-powered tools, such as intelligent tutoring systems, AI-integrated learning management systems (LMSs), and Large Language Models (LLMs), which support synchronous and asynchronous collaboration in higher education and MOOCs [44].Tools like ChatGPT, Google's Socratic AI, and adaptive learning systems (e.g., Squirrel AI) were highlighted as facilitators of real-time peer-to-peer learning, co-authoring, and cross-institutional knowledge exchange [45].In addition, 12 studies emphasized that institutions participating in multi-university online courses, joint AI curriculum design, or research projects benefited from automated content generation, collaborative assessment tools, and AI-powered discussion boards. This trend was most prominent in STEM and computer science programs, but some applications in social sciences and language learning were also reported.

However, the review also noted that resource disparity and lack of standardized AI infrastructure in low-income regions remain barriers to broader collaboration [46].Figure 9 illustrates the three key domains where AI fosters collaboration in education: teaching collaboration (e.g., joint MOOCs, AI teaching assistants), research collaboration (e.g., co-authoring, shared datasets), and peer interaction (e.g., multilingual group projects, collaborative grading). This radial diagram captures how AI tools are actively bridging institutions, learners, and educators to enable more connected and scalable educational practices.

Figure 9

AI-Enabled Collaboration Use Cases in Education

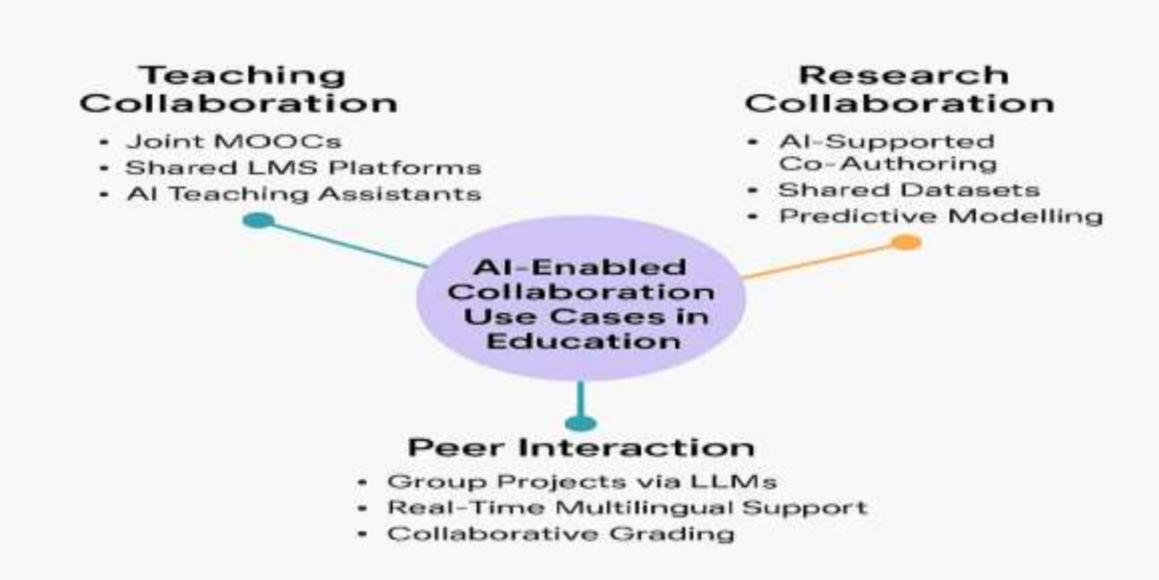


Table 9 presents a summary of the most frequently mentioned AI tools supporting collaboration in the 62 reviewed studies. It highlights how platforms like ChatGPT, AI-enhanced LMSs, and MOOCs are being used for joint teaching, peer learning, and cross-institutional research. The table also shows the number of studies referencing each tool, emphasizing that LLMs and explainable AI systems are the most widely adopted for enabling collaborative practices in higher education.

Table 9

AI Tools Supporting Collaboration Identified in the Review [47]

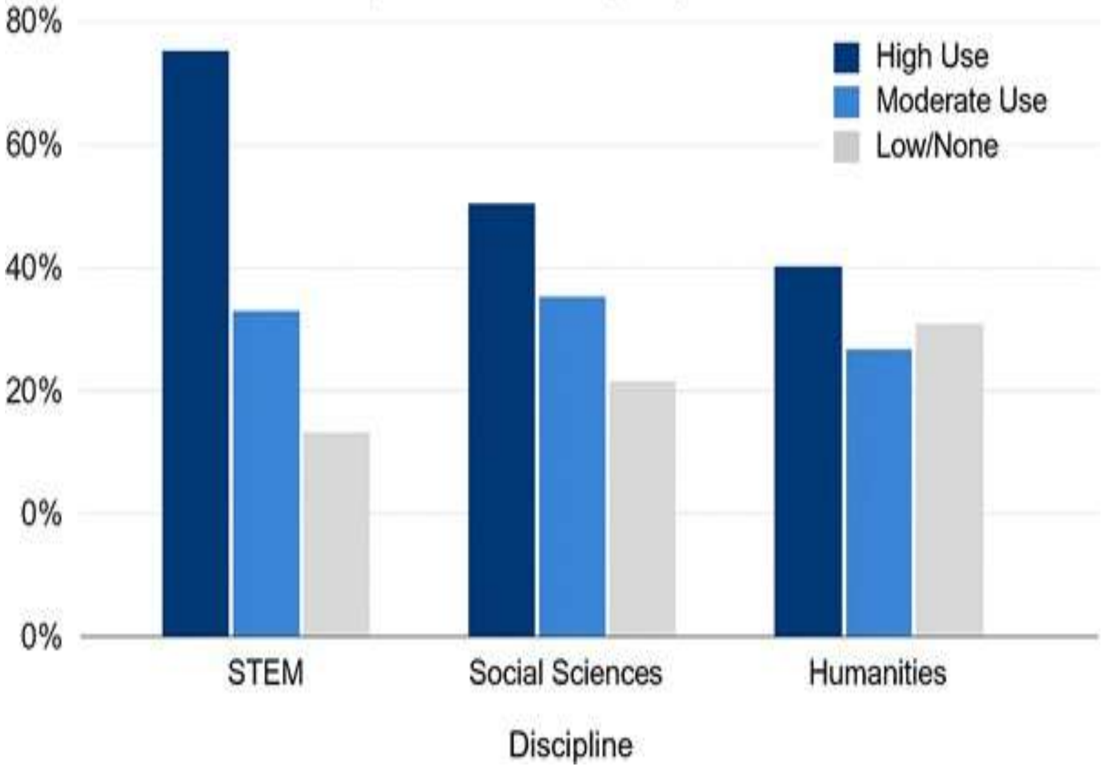
AI Tool / Platform	Purpose	# of Studies
ChatGPT / LLMs	Peer collaboration, drafting, Q&A	9
AI-enabled LMS (e.g., Moodle+AI)	Joint course delivery, feedback automation	7
MOOCs (Coursera, FutureLearn)	Shared teaching modules, multilingual content	6
Slack / MS Teams + AI bots	Collaborative research and teaching coordination	5
Adaptive Learning Systems	Personalized collaborative problem solving	4

Note. This table summarizes the AI tools and platforms most frequently reported in the reviewed studies as supporting collaboration in education. The tools facilitate diverse functions ranging from peer interaction and multilingual content delivery to research coordination and adaptive learning.

Figure 10 presents a bar chart comparing the adoption of AI collaboration tools across academic disciplines based on the 62 reviewed studies. It shows that STEM fields lead with the highest level of AI integration (68% high use), followed by social sciences with moderate adoption, and humanities, which display the lowest uptake and highest percentage of low or no use (32%). This trend suggests that while AI-supported collaboration is gaining traction in all areas, technical and computational disciplines are currently benefiting the most.

Figure 10

Discipline-wise Adoption of AI Collaboration Tools (Based on 62 Papers)



RQ5: What machine learning (ML) models are most frequently used in education, and how do they contribute to student outcomes?

Across the 62 studies reviewed, machine learning (ML) models were used in 38 papers to support various educational goals, including performance prediction, adaptive learning, dropout detection, and intelligent tutoring. Decision Trees (DTs), Random Forests (RFs), Support Vector Machines (SVMs), and Neural Networks (NNs) especially deep learning models such as LSTMs and CNNs were the most commonly used models. These models were mainly used to categorize student success, give individual feedback, and decompose learning behavior based on the interaction logs or assessment information [48].

Regarding impact, 24 studies indicated that ML models resulted in better learning outcomes (an increase in retention rates, better grades, and earlier interventions of at risk students). For example, a recent evaluation using Portuguese secondary school data found that neural networks and random forests achieved top predictive accuracy of approximately 87.4 % and 85.6 %, respectively [49]. Another systematic review confirmed that Random Forest, SVM, and Neural Network models are the most frequently used techniques to enhance personalized student guidance, particularly in career recommendation systems [50].

Additionally, a new comprehensive study applied eight advanced ML models including DTs, RF, KNN, XGBoost, and CatBoost to educational data and found that CatBoost achieved the highest accuracy (~87.5 %), outperforming Decision Trees (82.4 %) and Gradient Boosting (87.3 %) in early identification of students needing intervention [51].Table 10 highlights the most popular machine learning models applied in the 62 educational studies reviewed and their particular applications and advantages. Their interpretability and predictive ability had often led to the selection of decision trees and random forests, whereas neural networks and SVMs were deployed to the more complicated problems of adaptive learning and personalization. These models have also enhanced the improved performance of the students through early warning systems, forecasting their performance as well as designing the learning experience as indicated in the table.

Table 10

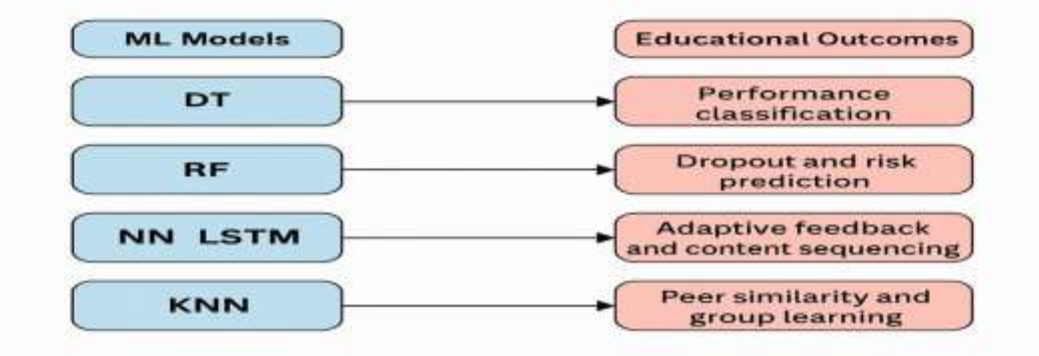
Most Common ML Models Used in Education and Their Applications [52]

ML Model	Application in Education	# of Studies	Reported Benefit
Decision Trees (DT)	Student performance classification	9	Easy interpretation for educators
Random Forest (RF)	Dropout prediction, learning outcome prediction	7	High accuracy, Robust to noise
Support Vector Machines (SVM)	Personalized learning recommendation	6	Works well with small to medium data.
Neural Networks (NN)	Adaptive learning, temporal pattern analysis	8	Robust in handling multifactorial and interdependent patterns.
Logistic Regression	Early warning systems	5	Simple, Interpretable
K-Nearest Neighbors (KNN)	Student grouping, Behavior clustering	3	Beneficial in exploratory settings

Figure 11 demonstrates the contribution of various machine learning models to particular education outcomes. As an example, the Decision Trees and the Logistic Regression are typically applied to classify student performance, whereas the Random Forests and the SVMs are implemented to predict the probability of dropouts. Neural Networks and LSTMs with adaptive feedbacks and content sequencing, KNN with peer grouping on learning behavior. The figure points at the point of correspondence between model capabilities and educational objectives.

Figure 11

ML Models Mapped to Educational Outcomes

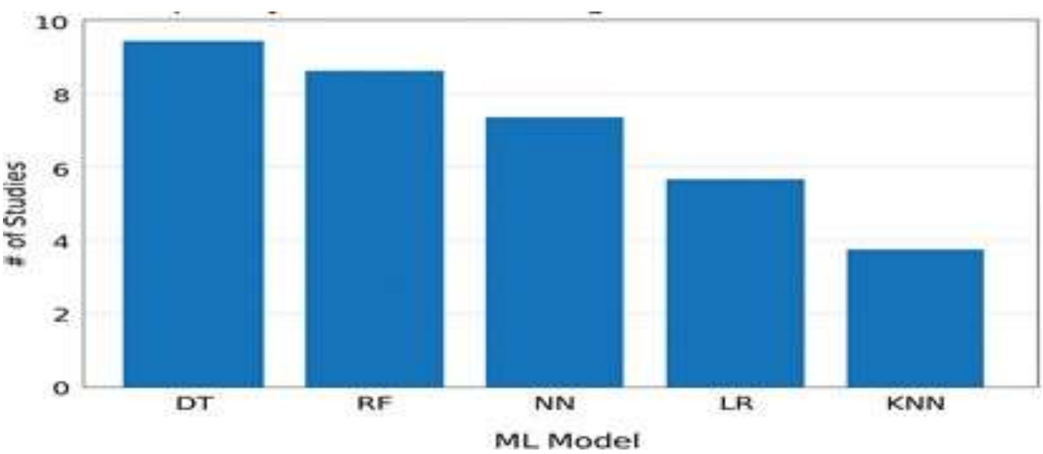


Note. An illustration of concept map of ML models (left) linked to essential outcomes (right) through arrows.

Figure 12 indicates how often machine learning models were employed in the 62 studies reviewed. The most widespread were Decision Trees (DT) and Random Forests (RF) which implies that explainable and precise models were favored in the educational context.

Figure 12

Frequency of ML Model Usage in Reviewed Studies



Note. This figure shows how often machine learning (ML) models are used in the 62 studies of the systematic review. The most common ones were Decision Trees (DT), Random Forest (RF), whereas Neural Networks (NN) may be listed as significantly used in the domain of complex educational tasks. The less frequently used but appreciated in interpretability and exploratory use were Logistic Regression (LR) and K-Nearest Neighbors (KNN).

Discussion

Adoption of AI in Secondary and Higher Education

We discovered that AI education use in both secondary and university levels have surged in the past few months, cutting across the computer science and non-computer science fields. This observation indicates that AI is ceasing to be an isolated field of study in high-level computer science but is turning into a multi-disciplinary topic taught in a wide variety of educational settings. The trend is in line with the recent studies. In their article, [51] described how AI has been incorporated into the curriculum of general education in China and Finland, since a transformation towards teaching students basic AI awareness has occurred across the globe. Also according to [52] the reforms of the curriculum in the United States and India are also AI ethics, problem-solving, and creativity orientation, therefore, AI is more significant than the technical knowledge. These results confirm our observation that AI education is spreading in several areas.

There are a number of things that seem to be fueling this growth. First, AIs realizing that they are modeling the daily life of society and the trend makes AI literacy interesting to policy-makers and educators [53]. Second, AI has become the most important element of the digital education policy designed by the governments, especially in Europe and Asia. Third, AI teaching tools have increased the accessibility of AI to students and teachers who do not have a technical background. In the tradition of Teachable machine, a project developed by Google, learners can build simple AI models using little to no code, and learners in AI + Ethics coursework can become familiar with such issues of AI systems as bias, fairness and transparency [54]. These resources reduce entry barrier and encourage large scale entry.

Our findings, therefore, suggest that AI education is shifting from a niche area in computer science to a mainstream educational component aimed at preparing students across disciplines for an AI-driven society.

Pedagogical Strategies and Training Tools Gaining Momentum

We have examined 44 studies and found that there is an apparent pedagogical change in the traditional lecture-based learning and teaching method to experiential and student-centered approach to AI learning and teaching, especially at the university level. Flipped classrooms, collaborative coding rooms, and AI based intelligent tutoring systems were all repeatedly reported to improve student engagement, understanding of concepts and their practical use of AI concepts. This observation represents a growing awareness that lectures alone are not sufficient to prepare students with the skills required to work in an AI-driven workforce.

Scratch as an AI tool and block-based programming environments in the secondary school level enable students to understand basic concepts of AI without knowing more complex programming languages. Jupyter Notebooks, integrated learning management system (LMS) plugins based on AI-driven feedback, and collaborative tools (like GitHub Classroom) became quite popular in higher education to enhance hands-on learning. These technologies will make AI more democratic by making coding and model experiments more accessible to a larger group of learners.

Recent empirical studies substantiate this tendency. Likewise, recent research has shown that AI-based tools such as adaptive LMS plugins not only enhance student motivation but also help close the AI skills gap among learners with limited programming experience [27]. Besides that, the effectiveness of flipped classes and collaborative problem-solving in improving both conceptual knowledge and team-building skills in AI learning has been emphasized [55] . Similar results were reported, highlighting that implementing AI-enhanced learning environments fosters self-regulation and creativity, skills essential for the 21st century [56].

These findings have two implications. First, the movement towards experiential learning strategies suggests that teachers are becoming aware of the role of active learning in training students to work in AI-related professions. Second, the popularization of training technologies in secondary and higher education implies that inclusive AI literacy is becoming the trend, and learners with low levels of computational abilities will be less likely to encounter challenging experiences.

Ethical Concerns and Responses to AI in Education

We have found that ethical issues in relation to AI in education were being directly noted in 34 of the 64 studies reviewed. The most controversial were risks of information privacy, algorithm partiality, absence of transparency, and the risk of excessive use of automated systems. The concerns suggest that despite the growing implementation of AI tools in classrooms, some essential questions about their fairness and accountability are still open.

These fears are supported by recent scholarship. AI-based assessment instruments often lack transparency in decision-making processes, which can reduce trust between learners and teachers[57]. Individualized learning AI systems add to existing inequalities especially those who are of low-resource backgrounds or of underrepresented communities [58]. The fact that current AI systems can lead to the risk of enhancing social biases is also consistent with our results, provided that they are not applied without sufficient precautions. The responses that were taken in the literature are modest and vibrant. A few of these organizations have already begun testing technical defenses, such as using differential privacy, transparent (white-box) AI systems, and bias monitoring systems [59]. At the pedagogical level, six studies analyzed included the introduction of AI ethics course within the curriculum and included fairness, responsibility, and responsible use. The teaching strategies based on case are aimed at assisting the students in questioning the negative facts concerning the AI and its impact on the society[60]. These endeavors are encouraging, as they are an indication of a shift between merely being aware of risks to the positive creation of ethical literacy among future practitioners. There are two implications of these findings. On the one hand, they repeat that there is an acute need to create multidimensional solutions to create justifiable and acceptable applications of AI in education, including technical, institutional and curricular. Second, they show that the training of knowledgeable digital citizens is the reason why the teaching of AI ethics in secondary and university schools is necessary. That is why the world bodies including UNESCO (2023) are insisting on policy frameworks which make transparency and fairness a fundamental value of AI in education.

AI for Fostering Institutional Collaboration

We identified 21 articles, which reported on the rising significance of AI in the process of institutional collaboration in research and teaching, specifically in online and technology-enhanced learning. These articles emphasize the fact that AI is altering the individual learning experience and also allowing cross-institutional cooperation. There is an increment of working together among the institutions through researchers and instructors to exchange knowledge and resources. They design their own curricula, assess data, and share teaching with AI tools such as large language models (LLMs) such as ChatGPT, AI-powered discussion boards, and common virtual laboratories. These tools worked especially well in the development of collaborative spaces. These tools can help faculty and students located geographically apart to work on collaborative projects, co-create course content, and analyze educational data together. This type of practice is changing the model of collaboration between the traditional institutional silos to open, networked academic communities. The latest studies appear to support the trend. AI has been applied in making massive open online courses (MOOCs) collaboratively in European universities, which has increased access to quality education in any part of the world [16]. Code review, literature review, and documentation of experiments at the postgraduate stage have been made easier now due to the integration of such tools as GitHub Copilot and Slack+AI into collaborative research processes [61]. Collectively, these results reinforce our observation that AI is becoming more and more a driver of institutional collaboration.

These results have important insinuations. First, they assume that AI can be used as a strategic mediator of global academic networks and reduce barriers caused by geography, unequal distribution of resources, and disciplinary cocoons. Second, they highlight the idea that AI-enabled collaborative infrastructure should be invested by universities not only to make knowledge sharing possible but also to prepare researchers and students to operate in the cross-border academic ecosystems of the future.

Machine Learning Models and their Educational Impact

Among the analyzed set of papers (62), 38 studies involved machine learning (ML) models to enhance educational results further. Decision Trees, Random Forests and Support Vector Machines (SVMs) and Neural Networks, including the world-state-of-the-art Long Short-Term Memory (LSTM) networks were the three most popular. These frameworks have been applied in an extremely diverse range of educational environments to predict student dropouts, customize learning, and automate the evaluation of performance. As per our findings, ML models are gradually being considered as a way of data-driven educational decision-making.Recent researches support this tendency. According to the researchers, both deep learning and Random Forests scored at least 90 percent when it came to the early-warning systems that would identify at-risk students. Neural networks can successfully predict academic performance using demographic and behavioral variables, as well as when working with smaller and imbalanced datasets [62]. The findings highlight the increasing trustworthiness of the ML-based educational analytics.

Nevertheless, in the light of these achievements our review found a severe limitation, namely interpretability has not yet been developed. Explainable AI (XAI) techniques, which include SHAP or LIME, were explicitly used in only 8 of the reviewed studies to explain model predictions. This is a worrying gap because to gain confidence in an AI-based recommendation, educational stakeholders (teachers, administrators, and policy makers) will need clear explanations behind automated decisions. This concern has been reflected in recent literature: SHAP explanations were shown to increase educators' confidence in AI predictions [63], while the lack of Explainability was identified as a barrier to AI adoption in schools[64].

Although ML models are becoming effective in predictive analytics and personalization in the education sector, it is clear that achieving their potential over time requires the transparency and interpretability of their predictions. It is feared that even with the high accuracy of AI pipelines, unless the Explainability is embedded within them, such models will not be perceived as effective by teachers and will not be accepted at the policy level. The XAI frameworks must not be implemented due to the technical requirement but rather a condition to the responsible and sustainable implementation of ML in education.

Challenges and Considerations

Even with its capabilities, the flexibility of AI in various educational settings has been an issue. As an illustration, AI software might not handle highly specialized or subtle ideas in computer programming or high-level science, which restricts its usefulness.

Conclusion

This systematic review pinpoints the revolutionary role of AI in redefining contemporary education and showing how it can transform contexts of both secondary and higher education and the ways it can be used to transform the practice of teaching, learning, and interdisciplinary approaches. The results reveal that AI in education has become quite popular not only in the context of computer science training but also with the fields of non-technical discipline, which are supported by easy-to-use tools and curriculum changes. The pedagogical transition to project-based learning and intelligent tutoring has become more engaging to the students, and it is supported by an expanding ecosystem of AI-powered platforms and training materials.

Although AI has significant potential, other emerging ethical issues were present especially privacy, bias and transparency which were noted by the review. There is an increasing interest in dealing with them, however, by policy-based and ethics-focused teaching, which remains limited. Also, AI has shown to be efficient in establishing collaboration among institutions via common MOOCs, research portals, and intelligent communication solutions. Machine learning models are extensively applied in the field of academic performance prediction and personalized learning, yet their low Explainability does not contribute to the further acceptance and adoption. Altogether, AI is constantly redefining education and provides novel chances to be innovative, more equitable, and cooperate internationally, but still requires careful regulation and non-discriminatory application.

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