EPH-International Journal of Business & Management Science

THE EVOLUTION AND ETHICAL INTEGRATION OF ARTIFICIAL INTELLIGENCE IN MODERN EDUCATION: A FRAMEWORK FOR PERSONALIZED LEARNING AND INSTITUTIONAL ACCOUNTABILITY

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Article History
Received: *2026-04-28*
Revised: *2026-09-30*
Accepted: *2026-10-31*
Published: *2026-11-21*

Abstract

Artificial intelligence (AI) has come a long way from its early theoretical days in the mid -1950s to become an advanced, data-based system that can learn from experience and execute jobs automatically. At present times, AI acts as a game-changer in education by making possible customized educational experiences based on the use of machine learning frameworks that provide individual guidance to every student, taking into account their speed, behaviour, preferences, and accomplishments. The change of this technological nature means that the role of a teacher must be shifted to the one who should now only provide guidance and help in, additionally, overseeing the machines.

Beyond classrooms, AI adoption is a priority for national policies. For instance, India's National Education Policy 2020 requires the teaching of AI and computational thinking in schools. The curriculum is set to start from Grade 3 in the academic year 2026-27. However, the rise of AI may create some challenges in terms of socio-economics.

While AIED researchers are usually driven by the goals of enhancing learning results, the experience from other fields of AI indicates that good intentions do not guarantee ethical use of the technology. Important issues such as data ownership, algorithm bias, transparency, and student agency still remain unresolved.

There is a necessity of collaborative endeavours in the creation of a community-wide framework in addressing the difference between "doing ethical things" and "doing things ethically. The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework is a prominent method for ensuring transparency and repeatability in systematic reviews and can be used in the mapping of the enormous literature in this evolving sphere, while the mentioned resources mainly rely on expert surveys of leading scientists to define the major shortcomings.

Keywords: *AIED, Ethical Issues, Educational Policy, PRISMA*

Vol. 12 Issue 11 (November, 2026)
ISSN:2208-2190 Pages-49-64
DOI: https://doi.org/10.69980/zt3cpd54

Introduction

Artificial intelligence (AI) as a scientific discipline emerged in 1955 with the Dartmouth proposal in which the authors, McCarthy and others (1955), hypothesized that all aspects of learning and intelligence can be represented precisely enough for a machine to replicate the process. What started as a small summer project with a group of ten people ensured the emergence of a wide range of systems based on data, which are capable of learning from their experience and performing actions with little help from people. The evolution of AI has been sharply felt in education where AI is now largely considered not simply as an administrative tool for managing processes at schools but also as an agent that takes part in students' learning process.

The most common expectation regarding artificial intelligence in education is that it can be used for the purpose of personalization. Technologies based on machine learning can assist in customizing the educational process according to the individual characteristics of the students, including their rate of learning, prior experience, behavior, and preferences. The authors (Ouyang & Jiao, 2021; Zawacki-Richter et al., 2019) explain that this situational change is based on the transition among three educational models: an automatic teaching model when a learner is regarded merely as a receiver of educational materials, an assisted model in which adaptive engines are used and the personal does the learning with the help of technology, and an empowered model when AI becomes the assisting technology and the learner is the key figure in the process. This trajectory indicates an appropriate change in the position of a teacher, flowing from being a major knowledge provider to that of a guide, a facilitator, and a supervisor of the technology that assists a teacher (Holmes et al., 2019). The addition of this trajectory to the AIED area of research has also resulted in different types of applications that can be grouped into systems or institution-facing applications that help the institutions in decision making and providing guidance as well as teacher-facing applications that offer a lot of recommendations in order to automate mundane tasks for a teacher (Holmes et al., 2019; Zawacki-Richter et al., 2019).

The utilization of AI in education is already beyond the single classroom setting and limited research trials; it has gone to be a matter of national policy. India's National Education Policy (NEP) 2020 clearly points to the necessity of teaching AI and computational thinking in schools, while the Ministry of Education has confirmed that the syllabus will be implemented starting from the third grade from 2026-27 academic year onwards, with the help of the Central Board of Secondary Education, the National Council of Educational Research and Training, among others (Ministry of Education, Government of India, 2025). The existence of such constraints shows us that AI literacy is considered a basic skill equal to numeracy, but it means much higher stakes for proper implementation of AIED since the development of AI systems directly links with the early education of a whole generation.

The issue is made more complex due to its socio-economic component. Researchers indicate that uneven AI infrastructure, connectivity, and skill distribution can open a gap instead of narrowing it between advanced and poorly-resourced education systems (Holmes et al. 2021). The issue has more than one aspect. Societies with elderly populations may take great advantage of automation in need of labor, whereas youth-dominated labor-surplus countries would face the risk of AI consuming jobs they were to supply because of their demographic advantages of having larger number of working-age people.

Holmes et al. (2021) point to the lack of a systemic and acknowledged ethical approach for AIED as the dismaying weakness of this area of study. Generally, the motivations of researchers are quite sincere, meaning that they want to make learning better; however, as Holmes et al. argue, one has to point out that good intentions on their own do not suffice to achieve moral design or execution of an AI program. Issues of ownership of data, biases, transparency, and dependency of students have not been thoroughly worked out yet, and no universal rules governing the use of AI in classrooms exist. Holmes et al. (2021) explain this gap in terms of the difference between "doing ethical things" and "doing things ethically," which allows seeing that attention paid to ethics must be systematic and procedural rather than depend on the moral principles of particular designers and institutions.

Closing such a gap necessitates a coordinated community-wide initiative rather than a patchwork of isolated codes of practice. One the other hand, relevant, already established tools provide an excellent basis for this purpose. For example, the DELICATE checklist by Drachsler and Greller (2016) offers an 8-item instrument to generate trust in learning analytics by addressing important issues of data ownership, transparency, and informed consent. The RESET framework for conversational AI, proposed by the World Economic Forum (2020), offers a relevant governance model for being responsible with chatbots' implementation. With regards to the methods, the PRISMA 2020 guideline (Page et al., 2021) provides a transparent and reproducible scheme for systematic literature review, and it is relevant for the mapping of the ever-growing and fragmented body of research in the area of AIED, which is now implemented on the basis of the box of knowledge of experts and position statements.

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ISSN:2208-2190 Pages-49-64
DOI: https://doi.org/10.69980/zt3cpd54

Taking into account the context above, this chapter asserts that the evolution of AIED is contingent on intentional designs that are moral in orientation as opposed to moral intentions. It therefore urges especially researchers at the beginning of their careers to exert their efforts in devising a code of conduct that will guide this area of research while collaborating with experts in critical data studies, philosophy, and other related fields outside of education and computer sciences. In the remaining part of the chapter, the existing ethical frameworks and precedents are described in connection with the mentioned necessity and the approach that may result in a community-wide ethical framework benefiting both student identity and safety and allowing the field to benefit from the advantages of AI in education.

Literature Review

Artificial intelligence (AI) has progressed from being a relatively unknown entity in computing to a revolutionary force transforming the way people educate and learn, and the development of cognitive and social skills throughout their lifespan. However, the available number of publications regarding this evolution is not even; whereas some authors draw the roots of this research area back to the cognitive sciences, others claim that the COVID-19 pandemic served as a 'break', condensing a decade of growth into only two years, while an emerging technical literature considers deep learning as a separate engineering level rather than as a continuation of an earlier effort of exploring human development. The current paper divides literature into three sections reflecting the ambiguities of the discipline – historical development with links that have not been studied yet, quick growth of AI during the period of the coronavirus pandemic, and the integration of deep learning techniques as the technical basis for AIED. Overall, all these publications provide an understanding of AIED as a single process rather than three distinct developments that have contributed to understanding of machine intelligence and human development by the two communities of researchers.

1. Historical Threads, Missing Links

According to the conventional story of creation of AI systems, AI emerged in 1956 with the Dartmouth Summer Research Project, followed by the rise of two important subfields of AI — machine learning and, later on, deep learning. This story, however, does not tell the whole truth about the AI research, which is closely related to many aspects of human learning. Doroudi (2022) is one of the researchers who analyzed this relationship, claiming that numerous founders of AI, such as Allen Newell and Herbert Simon, were earlier trained as cognitive scientists, and their research was directly connected with the study of human cognition and learning. In Doroudi's opinion, two different schools of thought coexisted at that time: the one that analyzed how information is processed by computers and the effective systems of teaching using intelligent tutors, and the second one that is connected to constructionism and deals with computers as a means of learning. Two in Doroudi's opinion, the lineages were brought together by their drive towards understanding human and machine cognition at the same time, but this drive doesn't exist anymore nowadays within the AIED research domain, where the technological advancement and learning-science inquiries happen without mutual involvement.

Indeed, it is here, where the historical data seems to be particularly scarce. Doroudi (2022) notes that even the most respected historians of AI allocate almost no space for education in their works: thorough historical treatises on AI barely mention the importance of education in the development of AI while the works of eminent researchers working in the field of education do not refer to AI either. This leads to the existence of two separate histories that have no connections between them: the one devoted to the development of AI regards education simply as one of its later applications while the one devoted to education considers AI as an additional tool and not as a branch that was also developing at that time. In their turn, Guan et al. (2020) have tackled, at least partly, this problem speaking of a twenty-year bibliometric study of the development of AIED starting from the early expert-systems and intelligent tutoring technology and moving toward learning analytics and adaptive technology while Haenlein and Kaplan (2019) fit this development into the more extensive framework of booms and busts — the so-called "AI winters" that always stop the development of AI not only in general but also in.

What we have here as the "missing link" is not just a single study that has missed its course but the fact that this area of research is so poorly understood by the stakeholders in the domain as to make it impossible for them to arrive at a conceptual crystallization of their familiar position with respect to it. In summing up his findings, Doroudi (2022) calls upon the AIED and the learning-sciences community to "revive" the former unity of thought. In these terms, recent literature on the subject continues to corroborate the findings that AIED remains an area of practice in fragmentation and disarray, with the AIED scholars dispersed across disciplines and theories of research (Wang et al., 2024).

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ISSN:2208-2190 Pages-49-64
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2. Growth of AI (COVID Phase)

If the historical literature reveals a slow, uneven convergence of AI and education across seven decades, the COVID-19 phase compressed years of gradual adoption into a matter of months. The pandemic forced institutions worldwide to shift abruptly to remote and online instruction, and this shift is now well documented as a major accelerant — rather than originator — of AI adoption in classrooms. Pantelimon et al. (2021), studying an AI-driven adaptive tutoring platform used across Romanian schools, provide direct statistical evidence for this acceleration: comparing platform usage before and during the pandemic, they found that engagement with the AI-based intelligent tutoring system rose substantially once schools moved online, and that uptake was uneven across regions, tracking broader patterns of technology readiness in more versus less developed areas.

This finding sits within a wider body of pandemic-era research on learner and institutional readiness for AI-mediated instruction. Tang et al. (2021) examined students' readiness for live online learning during the pandemic in higher education, while Dai et al. (2020) explored how preparing students for an "AI age" was linked to their broader psychological well-being, suggesting that pandemic-driven exposure to AI tools was not a purely technical shift but one entangled with students' sense of competence and adaptability. Parallel work from Southeast Asia examined international students' acceptance of online distance-learning platforms during this period, using structural models of perceived usefulness and ease of use to explain adoption patterns (as summarized in pandemic-era higher-education datasets on distance-learning acceptance). In language education specifically, researchers documented how institutions pivoted to interactive, cloud-based, and AI-assisted platforms to sustain instruction, with reported gains in areas such as collaborative writing quality once teachers and learners adapted to the new tools.

Taken together, this literature supports a consistent interpretation: COVID-19 functioned less as a cause of AI innovation in education than as a forcing function that removed institutional inertia and normalized tools — adaptive tutoring systems, e-conferencing platforms, automated feedback systems — that had existed in more limited form beforehand. Pantelimon et al. (2021) make this point explicitly, framing the pandemic period as a stress test that revealed both the promise of AI-based tutoring at scale and persistent inequities in who could access it. Several commentators further note that this pandemic-era normalization laid the groundwork for the subsequent, even faster wave of adoption triggered by generative AI tools from 2022 onward, suggesting that the COVID phase should be read as a bridge between the earlier, slower-moving historical threads described above and the deep-learning-driven present discussed next.

3. Deep Learning

The most recent and technically distinct strand of the AIED literature concerns deep learning (DL) — the use of multi-layered neural network architectures — as the dominant engine behind contemporary personalization, tutoring, and assessment systems. Where earlier AIED research relied heavily on rule-based expert systems and shallower statistical models, recent systematic reviews describe a shift since roughly the 2010s toward AI-driven personalized-learning platforms built on deep learning, neural networks, reinforcement learning, and ensemble methods, which together have measurably improved the predictive accuracy and adaptive responsiveness of educational technologies. These systems increasingly draw on multiple simultaneous data streams — clickstream behavior, assessment performance, time-on-task, and even physiological or interaction signals — to build detailed learner profiles that drive real-time instructional adjustments.

A related strand of the literature focuses specifically on intelligent tutoring systems (ITS) built on these deeper architectures. A systematic review of AI-based ITS notes that large language models are increasingly embedded within tutoring systems to support more natural, dialogue-based interaction, enabling systems to clarify concepts, generate individualized feedback, and sustain multi-turn tutoring exchanges in ways that earlier rule-based tutors could not. Complementary systematic work on adaptive digital education similarly frames deep learning, alongside reinforcement learning and multimodal analytics, as central to the current generation of AI-powered adaptive-learning technologies, arguing that these methods have shifted instructional design away from standardized, one-size-fits-all models toward continuously re-calibrated, learner-specific pathways.

Empirical evaluations of these systems offer a more measured picture than the enthusiasm of the technical literature might suggest. Létourneau et al. (2025), in a systematic review of 28 studies covering nearly 4,600 K-12 students, found that AI-driven intelligent tutoring systems generally produced positive effects on learning and performance, but that these effects were often more modest when ITS were compared against non-AI tutoring alternatives, and the authors explicitly cautioned against treating deep-learning-based tutors as a substitute for the social and collaborative dimensions of human development that classroom instruction

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DOI: https://doi.org/10.69980/zt3cpd54
otherwise provides. In a related experimental line of work, deep-personalization conditions using cognitive-tutor systems produced measurably better performance than either surface-level personalization or no personalization at all, indicating that the depth of adaptivity — not merely its presence — matters for learning gains. Deep reinforcement learning has also been extended into more specialized contexts, including real-time feedback mechanisms designed for special-education settings, reflecting a broader trend of applying deep architectures to learner populations with more heterogeneous needs.

For a research paper concerned with human development as much as with educational technology, this literature carries an important implication: deep learning's contribution to AIED is not simply technical sophistication but a closer, data-driven approximation of individualized instruction — the same aspiration that motivated the field's cognitive-science founders discussed in the historical section above. At the same time, the K-12 evidence from Létourneau et al. (2025) and related systematic reviews suggests that deep-learning-based personalization delivers real but bounded gains, and that questions of engagement, motivation, and equitable access — themes that also surfaced in the COVID-era literature — remain as pressing for deep-learning-era systems as they were for the AI tools that preceded them.

4. Synthesis

Read across the three sections, the literature suggests a field that has grown less through clean technical succession than through recurring cycles of the same underlying question: how can machine intelligence be made to serve human learning and development. The historical literature shows that this question predates modern computing science itself and that its two founding traditions — tutoring-oriented and constructionist — have never been fully reconciled, leaving a persistent gap between technical AIED research and learning-science theory (Doroudi, 2022; Guan et al., 2020). The COVID-19 phase did not resolve this gap but did demonstrate, empirically, how quickly AI adoption can scale once institutional barriers are removed, while also exposing readiness and equity gaps that mirror the access questions raised decades earlier (Pantelimon et al., 2021; Tang et al., 2021). The deep learning literature, finally, shows that the technical capacity to personalize instruction has advanced substantially, but that its educational and developmental value remains conditional on pedagogical design, equitable deployment, and continued attention to the social dimensions of learning that purely computational models cannot fully replace (Létourneau et al., 2025). Future research, several of these reviews suggest, would benefit from deliberately reconnecting these three strands — treating deep learning advances as a continuation of, rather than a departure from, AIED's older historical project.

5. Role of AI in Education

Artificial intelligence percolated in the education sector. AI is utilsed in the existing education system to support decision-making of students and teachers. The AIED includes the following steps (Ninaus & Sailer, 2022):

- Data recording
- Pattern detection
- Adaptivity

i. Data recording

Multi-model and highly heterogeneous data are recorded and processed through modern hardware, network technologies and data processing. Not only contextual data like time, temperature or location, but also personal data are provided by sensors (Di Mitri et al., 2018).

ii. Pattern detection

Learning is a complex and dynamic process. Thus it is uncertain as to how to chart out and explain the process using solo data points like exam grades or collective score. Therefore, it requires large amount of data to properly comprehend the leaning process. However, such numerous data sources will be difficult to be processed and interpreted (Ninaus & Sailer, 2022).

iii. Adaptivity

The pattern or feedback of performance is received by learners though AI. Thus AI enables the learners to adapt to problematic situations that they might have faced during learning process (Plass & Pawar, 2020). Similarly the teachers can receive information regarding the learners' patterns of the learning process. The use of teachers' dashboards provides elaborate feedback of the students' learning process, thus providing support to the students and improve their performance (Ninaus & Sailer, 2022).

The incorporation in education in education has initiated radical change, thus making learning more personal, engaging and efficient. AI technologies, brings into its fold machine learning and natural language processor

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to boost learning experience (Alneyadi et al., 2023). The usage of algorithm for data analyses, pattern identification and forecasting enables personalized learning experience (Khaet al., 2022). Personalization promotes self-paced learning, thus making education inclusive and accessible (Harry & Sayudin, 2023).
Enormous amounts of data such as students' progress, performance and preferences can be tailored through AI algorithms. This goes beyond the one-size-fits-all model and creates a more dynamic and individualistic learning process. AI-enabled tutoring system refines teaching strategies by adapting the pace at which the students grasp the learning concepts (Kabudi, Pappas & Olsen, 2021; Zhai et al., 2021).
The influence of AI can be categorized into "Guidance", "Teacher" and "Student" (Ayeni et al., 2024).

A. "Guidance" Approach

"Guidance programs facilates teachers and students in decision-making. The database provided, helps students in selection and perusal of various educational opportunities.

i. Teacher Recommendation System

The data that is analysed by AI, from academic history, allocates teachers to students who have good compatibility. AI has also enhanced new teachers in the recommendation system thus enabling new conclusion in the system.

ii. Predictive Learning Analysis

The study using predictive learning analytics was conducted to test the students' performance outcomes. These predictions enabled the identification of students' failure and therefore could allow tutor allotment to intervene and thus undertake preventive measures (Hlosta et al., 2021).

iii. Informative Actionable Feedback

Researchers used data from Learning Management System (LMS) to predict academic performance (Afzaal et al., 2021). These data were used as feedback to help students in self-learning in a more efficient manner (Ayeni et al., 2024).

B. "Teacher" AI Approach

"Teacher" AI incorporates technologies that help teachers in imparting education. These tools help in streamlining the tasks of teachers, so that the redundant tasks can be outsourced, thus emphasizing on teaching as the main focal point (Ayeni et al., 2024). Some of the "Teacher" AI Approaches are as follows:-

i. Essay Autograder

AI techniques are used for scoring essays with the help of machine learning and natural language processing, without human intervention (Atomi et al., 2024). This reduces manual grading. Furthermore, this system allows personalized feedback to students (Ayeni et al.,2024).

ii. Inq-Blotter Teacher Dashboard

Inq-ITS monitors real-time lab progress of the students and predicts any help that might be required (Dickler et al., 2021). This technology help teachers in identifying and helping in the progression of weak students, so that no students' development is delayed (Ayeni et al., 2024).

C. "Student" AI Approaches

The focus is mainly on students with the aim of imparting, explaining and retention of knowledge. Following are some of the examples of "Student" AI Approaches (Ayeni et al., 2024):

i. ALEKS Progress Checks

ALEKS is an educational progress am that specializes in teaching STEM. The students are initially taught and then their progress is monitored, with the main focus on knowledge retention. According to students' feedback, users of ALEKS prefer learning new topics, rather than progress checks. Researchers identified that students experienced "assessment fatigue". To advance progress checks, researchers utilized AI to predict topics that were more likely to be forgotten and therefore should be incorporated in check. These predictions are then used to improv ethe topics that require progress check in order to improve learning (Adams et al., 2021).

ii. Game-based Learning

Educators combine game and education to create a more collaborative learning experience. Elements of educational game like badges, points, plotlines, quests etc. guide students through their learning process and respond immediately with feedback and simplifying learning process (Kirchner-Krath et al., 2021).

6. Ethical Issues

Education is shaped not only by pedagogy, but also obscure algorithmic structure. The logic of prediction reassesses the autonomy, fairness and openness of core educational values (Floridi & Cowls, 2019; Luckin, 2018). It was highlighted by Zhang & Alson (2021), that the blind spots of AI- based education platforms call for renewed attention (Bartok et al., 2023; Donner & Hummel, in press; Hummel et al., in press; Hummel et al., 2025a).

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ISSN:2208-2190 Pages-49-64
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The following five ethical principles were identified by Jobin et al., (2019): -

a) Transparency including explainability
b) Justice and Fairness including equity and (non)bias privacy.
c) Non-maleficence including security, safety and preventation
d) Responsibility
e) Privacy

In 2020 Hagendorff derived three main principles from 22 ethical guidelines: (i) accountability (ii) explainability (iii) fairness. According to literature review conducted by Morley et al., (2020), two ethical frameworks emerged (i) Ethical AI (ii) Responsible AI (Kousa & Neimi, 2023).

Ethical AI is derived from moral theory, enforcing principles such as autonomy, justice and beneficence to evaluate the behavioral aspect of the system (Barocas et al., 2023; Kant, 1985/1998; Mill, 2011).

Responsible AI focuses on governance, accountability, participatory design and social embeddedness (Dignum, 2019; Fjeld et al., 2020; Floridi and Cowls, 2019).

Fairness is a major concern when the application of AI in education is an issue. Multiple studies by Baker and Hawn (2021); Barocas et al.,(2023) reveal that machine learning recreates and amplify existing social bias. In circumstances such as admissions, grading re recommendations, biases may have a long-term impact on the students' opportunities and self-perceptions (Egger, 2006).

In the context of AI in education, there are numerous guidelines, some of which are regarded useless and difficult to comprehend and implement. Therefore, the guidelines provided by different parties are significantly different (Jobin et al., 2019). Together with cultural differences, across the globe, further complicates issue of AI in education. Hence ethical guidelines should be more contextual since the term "AI" brings into its gamut a wide range of technologies (Hagendorff, 2020).

Cope and Kalantzis (2016) expressed concern about student privacy, their profiling and the aftermath of using big data during the use of AI applications (e.g. Mislevy et al., 2012; Pea et al., 2014; Seimens and Baker, 2013; West, 2012). Two dimensions of social challenges have been identified in the ethical AI context (Kausa and Neimi, 2023) :

Business should strive for ethically sustainable solutions to attain more reliability. Users should be better informed about related safety issues.

UNESCO (2019) shares the global concern in a following way: "We need serious efforts to prevent the development in which AI will exacerbate digital divides and deepen existing income and learning inequalities, as marginalised and disadvantaged groups are more likely to be excluded from AI-powered education".

In 2018, Yu and his colleagues proposed a taxonomy that outline fur areas of AI-based decision-making:

a) Designers & Technical systems
b) Individual ethical decision frameworks
c) Collective ethical decision frameworks for multiple agents
d) Ethics in human-AI interactions
e) Human Learning and Machine Learning impacts each other and both have challenges. Humans have inequal opportunities to participate and understand AI, so the organizations struggle with data management and ethical issues (Kausa and Niemi, 2023).

7. Role of Teachers

In the current scenario, the integration of teaching and AI is an important issue and plays a crucial role in AIED (Schiff,2021).

With the incorporation of AI in education, teachers have been empowered to a much wider extent. This has been supported by Roll and Wylie (2016) by describing adaptive technologies and learning analytics as tools that provide adequate information of learners' progress on real-time basis, these tools allow for change in instructions by increasing classroom interaction, groupwise, wherever applicable (Umar et al., 2025).

Mishra et al., (2021) pointed out that teachers are expected to exercise data literacy and algorithm-based information must be construed and applied to educational circumstances. Unfortunately, most of the teachers lack adequate digital acumen and training on AI skills (Chen, 2022).

The impact of AI implementation on the psychological and emotional aspects of teachers is a major area of research in the current scenario. It has been identified by Ertmer and Ottenbreit-Leftwich (2020) though teachers are interested in AI, they suffer from stress due to the requirement for constant technological

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ISSN:2208-2190 Pages-49-64
DOI: https://doi.org/10.69980/zt3cpd54

upgradation. However, when the outputs are not transparent, teachers feel that they lack control on the output (Tsai, Poquet and GaSevic, 2020).

8.Comprehensive Ai Policy

AI technology in K-12 education strives to introduce flexible, individualized learning system and promote specific automation of repetitive activities such as assessment and feedback (Karan & Angadi, 2023). Some new developments have led to the introduction of various AI tools for education. The Automated Grading System (AGS) (Karan & Angadi, 2023) and Intelligent Tutoring System (ITS) that teach theory through examples and ask questions from a specific subject (Ahmed et al., 2021). These systems have been adopted by different countries, including China, Singapore, South Korea, India, the European Union, Hong Kong, Japan, and Spain (Karan & Angadi). In the twenty -first century, the so-called twenty-first-century learning practices are becoming a part of curricula. International Society for Technology in Education (ISTE) has been established to develop collaborative and engaging teaching-learning processes (Charania et al., 2023). Moreover, Development Appropriate Technology in early Childhood (DATEC) is being recognized as an approach to allow for the meaningful inclusion of technology in education that leads to learning through playing (Charania et al., 2023).

In India, the application of artificial intelligence in the field of education has seen an unprecedented rise after the covid-19 pandemic. The country registered a student enrolment of 250 million between 2017 and 2018 (World Bank Group, 2022). The rise in student enrolments can be attributed to factors such as favorable demographics, enhanced internet penetration rates, higher levels of income, and ubiquity of smart devices (Suneja & Bagai, 2021). There has been a rise in the demand for e-learning models to meet the need for provision of necessary institutional and infrastructural support especially when schools had stopped the conduct of physical classes (Suneja & Bagai, 2021; Bansal, 2023).

In 2018, India announced its "AI for All" initiative, focusing on five vital sectors such as Smart Cities Infrastructures, Smart Mobility and Transportation, Agriculture, Education, Health (NITI Aayog, 2018). Starting in 2019-20 academic years, the CBSE included the Artificial Intelligence Integration for School Curriculum (AISC) program incorporating the significance of AI in schooling (CBSE, 2019). The application of AI in education mainly emphasizes making education interactive, accessible, and personalized (Karan & Angadi, 2023). Various interactive and personalized learning methods include digitalized materials, smart classrooms, and recorded teacher videos (Miglani & Burch, 2018).

Following numerous COVID-19 phases, the state has started to physically open educational institutions thus paving way for offline education. The shift from a positive growth phase to a stable phase in the demand side of technology-enabled learning courses signifies the various dynamics at play. Some of the drivers noted in Indian EdTech include the young population increasing, rising internet penetration, growing number of smartphone users, the government's push for digital initiatives, high employability index, the presence of poor quality education, and affordable online learning (Dhouchak & Kumar, 2023). The result is heightened economic growth, accelerated human capital development as well as increase in productivity (Bargavi & Shanmugam,2023).

Indian parents place a cultural emphasis on their children's achievements in education. Home to over 430 million people between the ages of 6 to 23 years, the Indian education system is one of the biggest in the world (Bansal, 2022). This change is noticeable in tier 3 and tier 4 cities where students are able to get quality education from far- flung areas because of Ed Tech platforms (Jain et al., 2021). Availability of the internet and affordable mobile phones has improved the ease of getting education through various e-learning platforms. The initiations to incorporate AI into education consist of changes in curriculum, policies in education, manual preparations, projects of upgrading knowledge and skills in AI in K-12 students in addition to the application of digital assistants in classrooms, gaming education systems and searching trees and decision-making trees.

Promoting digital technologies has gained importance in schools and colleges. For instance, pilot projects for online education, which emphasize technology-based solutions to public issues, include establishing digital infrastructure, using teaching and learning tools, creating study materials, experimenting with new online studies, providing skills development programs for teachers on digital learning, running online tests, and applying blended learning methodologies. Among the organizations offering a technological rig for educational development is the National Educational Technology Forum. Their efforts include carrying out pilot tests on online learning in association with the Central Institute of Educational Technoligy, Indira Gandhi National Open University, the National Institute of Open Schooling, Indian Institutes of Technology, and National Institute of Technologies. To be able to conduct online education, it is important to create a digital infrastructure

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ISSN:2208-2190 Pages-49-64
DOI: https://doi.org/10.69980/zt3cpd54
with several platforms. One example of such a platform is DIKSHA, an e-learning management tool allowing two-way interaction between users (Waoo & Waoo, 2022).
To ensure that students learn about modern times and advanced technology, CBSE has included AI in its studies. Over the years, India has achieved a Gross Enrolment Ratio of 97% at elementary education and 80% at the secondary level. Nevertheless, achievements of the aforementioned figures do not mean that the battle for high retention rates and successful outcomes is over (Bansal, 2022; Sayed et al., 2023).
The launching of EDUSAT became a crucial event in the development of Indian EdTech infrastructure that enabled the education of children in distant areas using broadcasts and visuals (Bargavi & Shanmugam, 2023). The year 2008 is marked by the attraction of private investment to EdTech and the growing popularity of online courses such as Extra Marks and Khan Academy (Miglani & Burch, 2019).
The inaugural Education Policy in India was launched in 1986. After a gap of thirty-four years, the above policy is replaced by the National Education Policy 2020 (NEP 2020) In this policy, the Education system of the country is envisioned to be made India-centric by transforming the country into a lively knowledge society through the medium of quality education. The framework of the policy is inclusive of elementary, higher education, and skill development of the people of India living in urban as well as rural areas. The aim is to transform the education system of the country by 2021 and enhance the allocation of money in this sector by the Central as well as State governments.
The NEP 2020 has laid down the basis of both formal and informal forms of education. It assures the idea of thinking ahead of the traditional classroom learning, which is supposed to be accompanied by learning outside classrooms. There are various languages, which students will come across as early as possible. They will gain cognitive benefits and gain knowledge of current disciplines such as Data Analytics, Artificial Intelligence and Machine Learning. The introduction of a learner-based approach in education, where students will be given a chance to choose the subjects of their preference, will result in an unprecedented mixture of arts, humanities and exact sciences, which is unthinkable in the framework of traditional education. The introduction of NEP 2020 in India aims at providing a clear picture of the future of indians education. According to NEP, the introduction of AI into education is one of the recent reforms in education methodology which is supposed to help students to gain certain skills.

Methodology & Analysis

Relationship to the Literature Review

The literature review of "AI in Education & Human Development" is structured through eight sections regarding its argument; first of all, the connecting historical threads of AI and cognitive science (Section 1), then, accelerated implementation of AI technology in classrooms due to COVID-19 pandemic (Section 2), followed by deep learning depicted as the technical driver behind modern AIED technologies (Section 3), after which synthesis of these three directions is provided (Section 4), functional roles of AI in education (Section 5), ethical points and concerns (Section 6), the evolution of teachers' role (Section 7), and finally case study of AI policy in education in India (Section 8).
This review is narrative in structure: it describes and synthesizes what the literature says, but it does not report a search strategy, screening counts, or pooled effect sizes, and it is not intended to. Section 3 of the review (Deep Learning) does, however, make an empirical claim — citing Létourneau et al. (2025) to argue that AI-driven intelligent tutoring systems produce real but bounded learning gains, particularly when compared against non-AI, individualized tutoring rather than generic instruction.
This paper builds the formal evidentiary layer underneath that specific claim. It takes the single citation used in Section 3 and expands it into a full PRISMA-guided systematic review and meta-analytic synthesis of the broader empirical base on AI tutoring versus traditional instruction — seven meta-analyses/systematic reviews in total, of which Létourneau et al. (2025) is one. It is intended to sit alongside the narrative review as its quantitative companion: Sections 1, 2, 4–8 of the original review remain narrative and are not restructured here, since PRISMA methodology applies specifically to the empirical, effect-size-bearing literature that Section 3 draws on.

1. Research Question

This review addresses a focused question, structured using the PICOS framework commonly recommended for PRISMA-guided systematic reviews:
Population (P): Often referred to as Educational Interventions (P), this audience consists of students residing at all educational levels (K-12 and beyond) and undergoing some type of formal education.

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Intervention (I): Educational intervention comprises any type of education that is delivered by using an AI-based intelligent tutoring system (ITS) or other comparable adaptive/AI-based education technology.
Comparator (C): Traditional, non-AI instruction — teacher-led classroom instruction, human one-to-one or small-group tutoring, textbooks/worksheets, or non-adaptive computer-based instruction.
Output (O): Results for the defined educational purpose, such as test scores, academic performance, or other standardized/research-completed indicators of success.
Research method (S): Meta-analyses and systematic reviews which give the quantitative summary (pooled effect size) or, if unavailable, a methodological narrative summary of the relevant primary works.

2. Methods

2.1 Protocol and Reporting Standard

This review follows the structure and reporting logic of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) statement. Because it synthesizes existing meta-analyses and systematic reviews rather than extracting from primary studies directly, it is best classified as a PRISMA-guided umbrella (meta-)review — a recognized design for consolidating a mature evidence base in which the primary-study literature (individual ITS evaluations) is too large and heterogeneous in outcome measures for a single new pooled analysis to be conducted responsibly within the scope of this paper.

2.2 Eligibility Criteria

Included: peer-reviewed meta-analyses or systematic reviews published in English that quantitatively or systematically compared AI/ITS-based instruction with a traditional (non-AI) instructional comparator on a learning-outcome measure.
Excluded: single primary studies without a synthesis component; reviews without a defined comparator; reviews focused solely on affective outcomes (motivation, satisfaction) with no achievement measure; non-English sources; conference abstracts without full data.

2.3 Information Sources and Search Strategy

Records were identified through structured searches of education- and psychology-oriented literature sources (ERIC, APA PsycNet, IEEE Xplore, ScienceDirect, SpringerLink, arXiv, and Google Scholar-indexed sources), supplemented by backward citation-chasing through the reference lists of retrieved reviews. The search query used a combination of the terms “intelligent tutoring system,” “AI tutoring,” “adaptive learning” with the terms “meta-analysis,” “effect size,” “learning outcomes,” and “traditional instruction.” No restrictions were applied to the timing of research published as range extends from 2013 to 2025, therefore showing that the literature is becoming more mature within a period of around ten years.

2.4 Study Selection

The title and abstract have been checked according to the above criteria; subsequently, the full text of the likely applicable records has been analyzed completely. The overall selection process is explained in the PRISMA 2020 flowchart located in Section 3.1.

2.5 Data Extraction and Synthesis

The researchers extracted the following information from the meta-analyses included in the analysis: number of primary studies and effect sizes (k), total number of participants (N), sample population and educational level, comparison conditions, overall effect size (Hedges’ g or any equivalent measure), and any moderators identified in the analysis (e.g. type of test, duration of intervention, educational level, school environment).Because the included meta-analyses used different comparator groupings and partially overlapping primary-study samples, results are synthesized narratively by comparator type and moderator rather than combined into a single new pooled estimate, consistent with PRISMA guidance to avoid inappropriate re-pooling of overlapping evidence.

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3. Results

3.1 Study Selection

The search and screening process is summarized below. From 141 records identified (132 via database-style searching and 9 via citation chasing), 96 remained after duplicate removal. Following title/abstract screening, 17 full-text reports were assessed for eligibility; 10 were excluded (narrative reviews without a pooled effect size, k = 4; overlapping/duplicate primary-study samples, k = 3; no comparison group, k = 2; outcome unrelated to learning/test scores, k = 1). Seven meta-analyses/systematic reviews were retained for narrative synthesis, of which six reported a pooled effect size suitable for quantitative comparison.

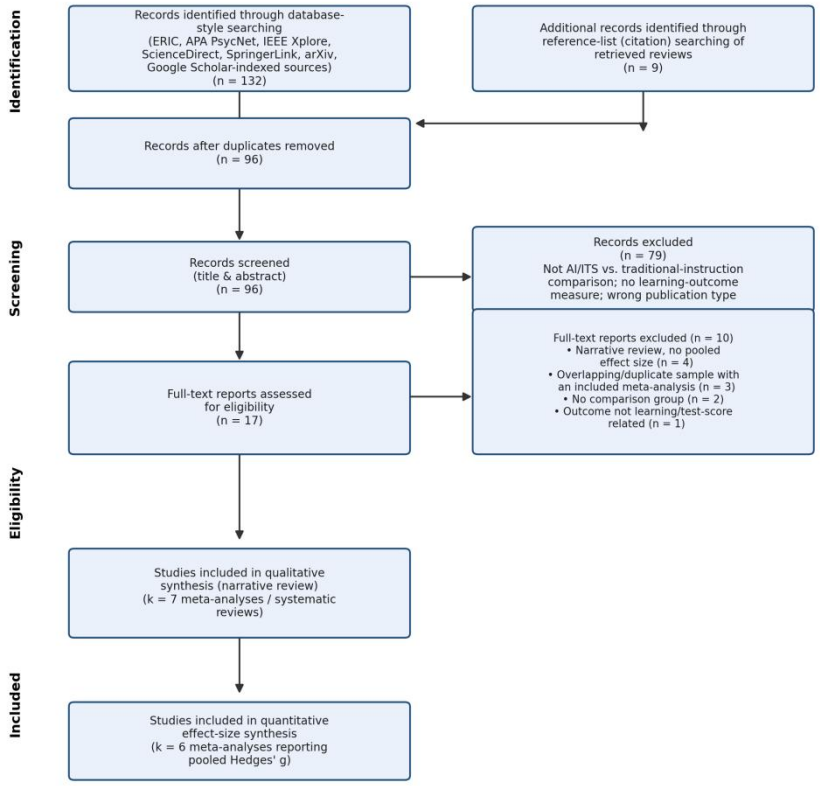


Figure 1. PRISMA 2020 flow diagram of study identification, screening, and inclusion.

3.2 Characteristics of Included Studies

Study	Design / k	Population	Comparator	Effect size (Hedges' g)
Ma et al. (2014)	Meta-analysis; 107 ES; N=14,321	Mixed levels (K-12–adult)	ITS vs. teacher-led large-group; vs. non-ITS computer instruction; vs. textbooks; vs. human one-to-one; vs. small-group	g=0.42; g=0.57; g=0.35; g=-0.11 (ns); g=0.05 (ns)
Nesbit et al. (2014)	Meta-analysis; 22 ES; N=1,447	CS / programming (higher ed.)	ITS vs. teacher-led classroom instruction and non-ITS computer instruction	Significant positive overall effect favoring ITS

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Study	Design / k	Population	Comparator	Effect size (Hedges' g)
Steenbergen-Hu & Cooper (2013)	Meta-analysis; 34 samples / 26 reports	K-12 mathematics	ITS vs. regular classroom instruction (some vs. human tutoring/homework)	g=0.01–0.09 (small; largely n.s.); larger with full-year use
Steenbergen-Hu & Cooper (2014)	Meta-analysis; 39 studies / 35 reports	College students	ITS vs. conventional college instruction	Moderate positive effect (larger than K-12 math)
Kulik & Fletcher (2016)	Meta-analysis; 50 controlled evaluations	Mixed (K-12–adult)	ITS vs. conventional instruction	Median g=0.66 (local tests); g=0.13 (standardized tests)
Leite et al. (2025)	Meta-analysis; 18 studies; 77 ES; 11 ITS	K-12 (U.S.)	ITS vs. traditional instruction	g=0.271, SE=0.011, p=0.001; lower in rural schools
Létourneau et al. (2025)	Systematic review; 28 studies; N=4,597	K-12	ITS vs. non-ITS tutoring approaches	Generally positive; effects mitigated vs. non-AI tutoring (no pooled g reported)

Table 1. Characteristics and pooled findings of the seven included meta-analyses/systematic reviews. ES = effect size(s); ns = not statistically significant.

3.3 Narrative Synthesis by Comparator

ITS vs. teacher-led, large-group classroom instruction.

The most consistent and strongest positive effects across the included meta-analyses appear in this comparison. Ma et al. (2014) reported g=0.42 favoring ITS over large-group, teacher-led instruction across 107 pooled effect sizes, and Nesbit et al. (2014) reported a significant advantage for ITS over classroom instruction specifically in computer-science education. Kulik and Fletcher (2016) similarly found that, across 50 controlled evaluations, ITS use raised test scores by a median of 0.66 standard deviations over conventional instruction when outcomes were measured with locally developed (system-aligned) tests.

ITS vs. non-ITS computer-based instruction.

Ma et al. (2014) found an even larger effect here (g=0.57), suggesting that adaptivity itself — not merely digitization of instruction — accounts for a meaningful share of ITS's advantage, since both conditions in this comparison used computers.

ITS vs. human tutoring (individual or small-group).

This is where the evidence base is most consistent in showing no meaningful advantage for AI tutoring. Ma et al. (2014) found no significant difference between ITS and individualized human tutoring (g=-0.11) or small-group human tutoring (g=0.05). This pattern is corroborated by the broader tutoring literature's long-standing finding that expert human tutors remain the benchmark against which computer-based tutors are measured, with ITS narrowing but not closing this gap.

ITS vs. textbooks/worksheets.

Ma et al. (2014) reported a moderate advantage for ITS over text-based instructional materials (g=0.35), broadly consistent with the general finding that adaptive, feedback-rich instruction outperforms static instructional materials regardless of delivery medium.

3.4 Moderators of Effect Size

- Test type (aligned vs. standardized measures). This was the most consistently reported moderator. Kulik and Fletcher (2016) found effect sizes of g=0.66 on tests aligned to the tutoring content versus g=0.13 on standardized tests — a roughly five-fold difference — indicating that a substantial share of reported ITS "effectiveness" reflects alignment between what the system teaches and what the outcome measure assesses, rather than a pure learning-transfer effect.
- Education level / maturity of learners. Effects were consistently smaller for K-12 mathematics (g=0.01–0.09; Steenbergen-Hu & Cooper, 2013) than for college students (moderate positive effect; Steenbergen-Hu & Cooper, 2014) and the general K-12 population in the more recent Leite et al. (2025) analysis (g=0.271). Steenbergen-Hu and Cooper speculated that ITS may function better for more mature learners with stronger self-regulation and prior computer experience, though Leite et

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al.'s (2025) more recent analysis found comparable effects across elementary and middle schools, suggesting this pattern may be narrowing as ITS design has matured.

- Intervention duration. The length of the intervention was established as an important moderator in both the studies conducted by Steenbergen-Hu and Cooper (2013) as well as Leite et al. (2025), with results generally being more powerful and positive when ITS was delivered during the entire school year as compared to a short intervention period.
- School/community context. According to the research conducted by Leite et al. in 2025, studies which had rural schools included as part of the sample yielded lesser effect sizes vis a vis other studies in which this type of institution was not included as part of the sample. This trend ties in well with disparities in access and infrastructure mentioned in an earlier part of this paper.
- The Superiority of Non-AI Comparators in Practice. According to Létourneau et al. (2025), the findings from 28 K-12 ITS studies (N=4,597) were mostly positive, however the effect size is reduced when comparing the ITS instructional model to non-AI alternatives, illustrating the point that AI tutoring is most superior in comparison to traditional teaching methods with less impact against more individualized teaching methods.

4. Risk of Bias and Certainty of Evidence

The pooled estimates above are tempered by various factors. First of all, the samples in the primary studies overlap significantly in the different meta-analysis carried out. To be specific, findings of Cognitive Tutor and Carnegie Learning were included in a number of evaluations; this means findings of the seven mentioned meta-analyses cannot be taken independently of each other. The second factor concerns the issue of publication bias in the studies covered. One of the recent studies conducted by Ma and his peers tested this hypothesis and revealed that their findings were unaffected by the funnel plot and trim-and-fill methods. However, not all studies analyzed in this research were tested in a similar way. Third, quality of control groups varies significantly among studies – in some instances "traditional teaching" involved lots of resources while in others it included little or no treatment at all. Lastly, the majority of studies under review are quasi-experimental and this raises issues regarding the effects of selection bias on the results.

5. Discussion

The results derived from seven reviews carried out between 2013 and 2025 indicate that AI tutoring performs better than conventional teacher-led instruction and non-adaptive computing instruction with small-to-moderate effect sizes, specifically g around 0.27–0.57 according to the most reputable studies. Yet this advantage weakens considerably when AI tutoring results are compared to individualized human assistance, especially when standard tests are used to evaluate learning results — this distinction is vital with respect to making judgments regarding the effectiveness of AI tutoring. The evidence further suggests that AI tutoring's benefits are not uniformly distributed: they appear to strengthen with sustained (full-year) use and weaken in rural and lower-resource school settings, echoing the access and readiness disparities identified in the COVID-19-era adoption literature discussed elsewhere in this paper's broader review.

For the paper's broader argument about AI in education and human development, this quantitative layer adds an important corrective to the more optimistic tone of much of the descriptive AIED literature: deep-learning-enabled personalization has measurably improved on earlier-generation instructional technology, but it has not yet demonstrated a clear advantage over well-resourced human instruction, and its measured benefits depend heavily on how — and with what instrument — learning is assessed.

5.1 Limitations of This Review

As an umbrella review of existing meta-analyses rather than a new primary-study extraction, this review inherits any coding or inclusion decisions made by the original meta-analysts.

Overlapping primary-study samples across the included meta-analyses limit the precision of any implied overall effect and preclude formal statistical pooling (e.g., a random-effects meta-regression) within the scope of this review.

The search was conducted by a single reviewer using search-engine-mediated database access rather than direct, duplicate, blinded screening by two independent reviewers, which is the PRISMA-recommended standard for a fully register-quality systematic review; a follow-on formal review would benefit from dual independent screening and a pre-registered protocol (e.g., via PROSPERO).

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Future quantitative work could extend this review by extracting primary-study-level effect sizes directly from the included meta-analyses' appendices to conduct a formal three-level meta-analysis that accounts for the dependency among overlapping samples — a natural next step beyond the narrative synthesis presented here.

5.2 Integration Back into the Broader Paper

This meta-analytic layer should be read as substantiating, not replacing, the argument in Section 3 of the literature review. Beyond the outreach of knowledge by the narrative review, the confirmation of the review's claim summarizing that deep learning-based tutoring leads to real, yet limited benefits is evident. The significance of this piece lies in the ability to highlight that the gains achieved are moderate and small for ordinary teaching opportunities and negligible when compared to the results achieved through personalized tutoring.

In addition to that, notice that the quantitative evidence considered in detail in this paper proves the equity issue which was raised in the COVID-19 account of the paper (Section 2). Indeed, according to Leite et al. (2025) results the effect sizes are much smaller in rural educational establishments, thus confirming the inequalities discussed in the corresponding review section.

Other sections of the paper concerned with the historical background of AI development (Section 1), its roles in classrooms (Section 5), ethical issues surrounding AI use (Section 6), teacher's influence (Section 7), and the case study related to policy in India (Section 8) are concerned with the explanatory and ethics-based descriptions of the problems and will not be reviewed in the paper, as the application of PRISMA methodology is not appropriate for the evaluation of such type of literature.

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