International Academic Institute for Science and Technology

International Academic Journal of Social Sciences
Vol. 13, No. 2, 2026, pp. 13-21.

ISSN 2454-3918

International Academic Journal of Social Sciences

www.iaiest.com

An Artificial Intelligence-Enabled Personalized Learning Framework for Sustainable Educational Development

Dr. Priya Sethuraman [a*]

[a] Professor, Department of Management Studies, St. Joseph's Institute of Technology, OMR, Chennai, Tamil Nadu, India. E-mail: priasethuraman@gmail.com*

Abstract

Personalised learning enabled by artificial intelligence is argued to be an approach to foster sustainable development of education. Evidence from meta-analysis demonstrates that AI-based adaptive learning yields higher cognitive gains than non-adaptive methods (g = 0.70) in terms of academic achievement (adding 0.36 standard deviation) and mathematics (adding 0.42 standard deviation), amounting to three to five months' additional learning. The meta-analysis on intelligent tutoring systems yields g = 0.86 on the basis of 30 studies, although its effects on motivation, knowledge and problem solving have not been conclusive yet. However, the connection between personalised learning and sustainable development is not as straightforward as it sounds – there is a lack of coherence in the concept of AI-enabled personalisation in terms of adaptive engines, learning analytics, and generative feedback. Likewise, the fields of AI in education and education for sustainable development have developed independently of each other without articulating the necessary conditions for the implementation of sustainable and lasting interventions. To remedy this situation, this paper introduces the AI-Enabled Personalised Learning for Sustainable Educational Development Framework, which is a multi-tiered framework consisting of learner modelling, adaptive instructional sequencing, human-in-the-loop teacher orchestration, and sustainable governance.

Keywords: Artificial Intelligence in Education, Personalized Learning, Adaptive Learning Systems, Sustainable Educational Development, Intelligent Tutoring Systems, Educational Equity, Learning Analytics, Teacher Agency.

DOI: 10.71086/IAJSS/V13I2/IAJSS1311
Received: 03 March 2026/Revised: 20 April 2026/Accepted: 12 May 2026/Published: 30 June 2026

Introduction

The issue of education is highly relevant within the framework of sustainable development goals because it acts as a goal in itself and as a condition for other goals. Goal four states that countries need to ensure inclusive and equitable quality education and lifelong learning opportunities for all, which can be provided with the help of advanced information technologies (Alamäki et al., 2024). Education technologies should consequently promote sustainability-based transformation (Abulibdeh et al., 2024).

However, AI is the preferred option because of its features of intelligent tutoring systems, adaptive learning, and educational analytics, where personalization is essential (Ma et al., 2014); algorithms and machine learning make the process of personalizing content based on engagement and performance outcomes (Crompton & Burke, 2023). In a meta-analysis of 45 articles, there was a medium to large effect ($g = 0.70$) related to cognitive outcomes and an increase by 0.36 SD in academic achievement and 0.42 SD in mathematics (approximately three to five months' worth of learning) (Chen, 2025). In intelligent tutoring systems, $g = 0.86$ was determined based on 30 articles and the largest effects were in attitudes to learning and test outcomes and not motivation and problem-solving abilities (Chan, 2023). Tutoring systems could improve performance by providing personal instruction and feedback (Kulik & Fletcher, 2015).

Nevertheless, there are two weaknesses from the perspective of sustainability. The first one is fragmentation, whereby adaptive engines, learning analytics, and feedback processes have been adopted separately without considering their relationship with each other and without paying much attention to the pedagogical and ethical contexts within which they operate. The second one is conceptual weakness, whereby the literature on AI and the literature on education for sustainable development have developed independently of each other (Adams et al., 2023), while research on their combination does not involve analyses of ethical concerns, impact of AI on education for sustainable development, and ways of their effective integration (Ayeni et al., 2024). The level of teacher trust in educational AI is also influenced by experience, perception, and educational contexts in various countries (Viberg et al., 2024).

Equity and ethics matter (Bond et al., 2024). Given the techno-solutionist paradigm, the current practice is most likely to result in inequalities and inequitable distribution of resources (Colchester et al., 2016), and the questions of consent, privacy, bias, fairness, accountability, and transparency should be resolved. The use of AI by teachers requires insight into how AI works and the preservation of professional autonomy via professional development (Ayanwale et al., 2024), and individualization can influence the outcomes as well (Wang et al., 2024). Thus, the paper explores how personalized learning can be designed, managed, and evaluated in order to ensure the match between cognitive development and sustainable educational development (Bhatta, 2026). Existing frameworks describe the capabilities of AI technology or the goals of sustainable development but not both, and we provide the framework of "AI-Enabled Personalized Learning for Sustainable Educational Development," which includes four levels (learner modeling, adaptive instruction sequencing, human-in-the-loop orchestration, and sustainability governance) and the requirements at each level (Bulathwela et al., 2024).

Literature Review

Adaptive Systems and Personalisation as the Dominant Application

Similarly to numerous other studies on the use of AI in HE, much attention is paid to the topics of adaptive technologies and personalization. According to the results of a systematic review, there were four main application domains of AI, such as profiling and prediction, assessment and evaluation, intelligent tutoring systems, and adaptive technologies and personalization, with very little contribution by teachers and educationalists (George-Reyes & López-Caudana, 2026). As reported by a tertiary review, the majority of reviews focused on AI in HE generally (47.0%) and AI and profiling and prediction specifically (28.8%) but failed to explore the common capabilities of AI (Memarian & Doleck, 2023). AI has a positive effect on students' performance (Dong et al., 2025) and contributes to personalized learning and educational administration (Zawacki-Richter et al., 2019).

Educational AI raises questions of privacy, fairness, and accountability that need implementation steps to be taken in order to address those ethical questions properly. It is important in relation to its implications for stakeholders such as policy-makers, researchers, and practitioners in the development of a well-effective, ethical, and inclusive learning environment (Ifenthaler et al., 2024), and can contribute to enhancing education quality and availability despite questions related to equity, ethics, and sustainability (Pedró et al., 2019), with latest developments providing more opportunities for educational activities (Zawacki-Richter et al., 2024).

They rely on learner models. Adaptive systems take into account the uniqueness of each learner's process, merging the recognition of learners' needs with the pedagogical know-how for addressing them; student models are created through the analysis of the affective state of learners, their level of knowledge, and personality traits and skills, thus supporting either the pedagogy of the designers or self-learning and adaptation of the system. A literature review of 63 studies regarding the application of artificial intelligence and machine learning in e-learning indicates that adaptive algorithms enhance learning paths, foster engagement, and lead to better academic results, although higher test scores have been indicated only in some of the reviewed studies, and there is an issue with privacy and complexity issues (Huang et al., 2025). Intelligent approaches in e-learning include machine learning, educational data mining, knowledge tracing, learning analytics, learner modeling, and intelligent agents (Gligorea et al., 2023), while democratizing AI in education means equal access and proper usage (Prinsloo & Khalil, 2024).

Evidence on Learning Outcomes

Meta-analysis is regarded as the strongest form of quantitative data. In 45 independent studies conducted in 18 scholarly databases, an AI-powered adaptive learning had a medium-to-large effect ($g = 0.70$) on cognitive learning outcomes in comparison to non-adaptive measures; publication type, country of study, level and major of learners, length of time, methodology of research, types of adaptivity (cognitive, affective, behavioral) and targets (navigation and assessment) are moderators of effect while the type of artificial intelligence is not. Meta-synthesis revealed 0.36 and 0.42 standard deviation improvements in general and mathematics achievement as opposed to traditional teaching approach with the magnitude similar to three to five months of extra learning (Steenbergen-Hu & Cooper, 2013). The meta-analysis of 29 empirical studies with 2,657 participants indicates a substantial positive effect of artificial intelligence on academic performance (effect size 0.924). The evidences that support intelligent tutoring are more complicated. Meta-analyses of 107 effect sizes involving 14,321 participants reported that ITS was more efficient than large group teaching by teachers ($g = 0.42$), computer-based learning ($g = 0.57$), textbooks/workbooks ($g = 0.35$), individual human tutoring ($g = –0.11$), and small-group teaching ($g = 0.05$). A review of 50 controlled experiments resulted in an average effect size of 0.66 standard deviations and strongly depended on the kind of local or standard tests used. ITS were moderately efficient in higher education ($g = 0.32$ to 0.37) and better than all other strategies except for human tutoring with the effect increasing with time. A meta-analysis of 30 studies ($g = 0.86$) revealed considerable improvements in learning attitude and test scores without any clear ITS influence on knowledge acquisition, motivation, performance, problem solving, or education level.

Sustainable Education and Ethical Conditions

Sustainable education is based on systematic acquisition of knowledge. There have been many researches that have pointed out the incremental inclusion of SDGs within the educational curriculum along with new issues in relation to AI and information technology (Nazaretsky et al., 2022). Yet, there is a need for more research on the ethical issues related to AI, personalization, and pedagogy of AI (Lin et al., 2023).

The ethics of integrating AI in education involve accountability, privacy, transparency, fairness, reliability, and learner autonomy (Nguyen et al., 2022). For K-12 education, there is also an additional focus on the rights of children, pedagogically appropriate use, AI literacy, teachers' well-being, explainability, and sustainability.

Teachers have a significant role to play in AI-assisted learning by assessing and adapting the suggestions made automatically. Explainable AI, together with professional training, can help address problems of trust and implementation on the part of teachers. There are other challenges, including workload issues, transparency of algorithms, new teaching approaches, and digital literacy (Roy, 2020). Additional research involving STEAM teachers highlights that AI literacy can mitigate biases and increase acceptance of AI-assisted assessments (Lucas et al., 2024).

Equity as a First-Order Design Constraint

Last but not least, the equity literature exposes risks associated with personalised learning through AI. If nothing changes, AI in education will increase the disparity between well-educated people and others because of techno-solutionism, meaning that technology is a quick and flawless solution. Bandwidth, devices, and AI literacies can increase the disparities that already exist, and the literature is primarily concerned with the use of AI in solving insufficient education rather than its role within the context of power and inequality, as well as what knowledge becomes legitimate, who benefits and who loses out. Positional work defines AI democratising education and education democratising AI; some of the solutions can be open-source material accessibility, training of educators, and interdisciplinarity.

Research Gap

This literature review points out three gaps influencing the significance of this study.

1. Integration gap. Adaptive engines, learner models, tutoring modules, and analytics are treated as separate interventions rather than parts of one learning system. Reviews of AI in higher education note that technical and methodological aspects are often explored but educational, ethical, and institutional integration is rarely addressed, with further barriers of cost, infrastructure, and unequal access to high-speed Internet.
2. Pedagogical–ethical gap. There is little critical discussion of pedagogical and ethical challenges of using AI in higher education, namely privacy, fairness, and learner autonomy. The FATE review shows that concepts have developed much faster than empirical studies, and similar challenges appear in the AI and education for sustainable development literature.
3. Sustainability-impact gap. Existing approaches do not link personalized learning outcomes, such as knowledge gain, motivation, and problem solving, with sustainability criteria, namely accessible learning, teacher competency, and institutional sustainability. While personalization can enhance learning, little is known about its wider impact, and without attention to digital access and skills, AI-driven personalization might widen the educational gap.

Contribution

This research will bridge this gap by introducing a novel AI-driven personalized learning framework that combines adaptive technology, pedagogical practice, ethics, and sustainability. The connection between personalized learning impacts and accessible learning, teachers' competency, and institutional sustainability would advance AI in education

Proposed Framework

Framework Components

Layer 1 – Learner Modeling. The first layer generates and updates the learner's multi-dimensional model. From the research into adaptive systems, it can be seen that the proper learner profile requires analysis of affective state, knowledge level, and personal skills and characteristics, and that the models not only support the pedagogy of the designers but also enable the system to learn and adapt the learning environment on-the-fly. This is because from the literature on adaptive systems it can be seen that the sources (cognitive, affective, behavioral) and targets (navigation, assessment) of adaptive systems mediate the effect of adaptation on learning, so that cognitive modeling alone would ignore sources of variation.

The governance layer imposes two limitations in this regard: information gathering should take into consideration the hesitancy of the learners to provide all information about themselves due to the fear of misusing it, and profiling should permit the testing of impartiality.

Layer 2 – Adaptive Instructional Sequencing. The current layer transforms the learner profile into actions such as content selection, task difficulty and pace adjustment, and assessments administration. This layer relies on evidence from moderators that navigation and assessment can be seen as adaptivity targets, and that the sources of adaptation span from cognitive to affective to behavioural. The results presented here represent the benchmark that the framework should preserve: a medium to large effect of the adaptive system on cognitive outcomes ($g = 0.70$), an improvement of 0.36 standard deviation on average and 0.42 in mathematics, and a positive effect of 0.924 based on 29 studies. Furthermore, the sequencing should adhere to the limits of evidence: the effects of ITS on-knowledge acquisition, motivation, performance, and problem-solving are ambiguous, while those on learning attitudes and tests are clear-cut.

Personalization Logic has to remain within the bounds of what adaptive technology is capable of, which is learning optimization, engagement, and improved testing outcomes, while being aware of the privacy challenges still ahead.

Layer 3 – Human in the Loop Teacher Orchestration. In this case, the teacher's judgement becomes structurally essential rather than optional. Teachers gain trust in AI systems if they know about the differences between AI decision-making and human experts' decisions and that the former complement rather than replace the latter, therefore requiring tools for teachers to critique, revise and, where necessary, override AI's decision-making before reaching the learner. Professional development is key in doing so as it increases awareness of AI-driven assessment, mitigates biases and misconceptions, and promotes adoption.

It also takes into account adoption barriers such as fear of radical changes in pedagogy, increased workload, lack of clarity in decision-making process by AI and a bias toward human rather than AI advice. Therefore, this layer develops three different interfaces for teachers, including recommendation review, override with explanation and cohort monitoring.

Layer 4 – Governance for Sustainability. This upper layer includes ethical, equitable and sustainable principles as constraints in the form of responsibility and accountability, privacy, neutrality, transparency, non-maleficence, precaution, and system reliability, as well as school-specific constraints of pedagogical appropriateness, children's rights, AI literacy and teacher well-being. Implementation requirements stem from comprehensive policy frameworks (accuracy, auditability, explainability, fairness, human-centricity and well-being, alignment with human rights, inclusiveness, progressiveness, robustness and security and sustainability). In this case, sustainability refers to preferences of implementations that provide sustainable insights. Responsibility and accountability are obligatory instead of desirable due to their role in legitimisation of AI adoption within organisation.

This is where the issue of equity comes to the fore. Since issues of uneven bandwidth, devices, and literacy can aggravate current inequalities and since technological solutionism may only widen gaps and inequities, standards of access and equity must be developed before implementation and outcomes are measured. One more issue that must be considered is that of AI literacy, which current definitions do not incorporate (see Table 1).

Table 1: Framework Layers, Functions, and Grounding Evidence

Layer	Primary function	Grounding evidence
1 Learner Modelling	Build multidimensional cognitive, affective, behavioural profile	Affective states, knowledge level, and personality traits as profile inputs; cognitive, affective, behavioural adaptive sources as significant moderators
2 Adaptive Sequencing	Select content, adjust difficulty and pacing, schedule assessment	Navigation and assessment as significant adaptive targets; g = 0.70 cognitive effect; 0.924 effect across 29 studies
3 Teacher Orchestration	Review, modify, and override AI recommendations	Teacher agency identified as key; override before recommendations reach students; PDP improved trust and reduced misconceptions
4 Sustainability Governance	Enforce ethical, equitable, and durability constraints	Principle sets in; bandwidth, device, and literacy inequity

Methodology

Research Design

The proposed methodology in question employs sequential mixed methods, using design-based research for fine-tuning the framework and a quasi-experiment for measuring its effectiveness. This is done in response to the criticism of AI-in-education studies that the area has been more concerned with technology than education and ethics, as well as to the preponderance of definitions over empirical studies of the concepts.

Participants and Sampling

Participants will be learners and educators at two educational levels, as the impact of adaptive learning on achievement changes depending on the learner's educational level and subject domain, while the effectiveness of ITSs does not have any significant relationship with the educational level but only with the country. Ethical tools that are appropriate for children will be used in school level settings.

Instruments and Data Sources

Data will be collected from four different sources: (i) logs for the performance and interaction of the platform, which constitute the behavioral data proven to be adaptive from previous studies; (ii) cognitive achievement tests, depending on whether they are standardized or local as the amount of improvement depends very much on that factor; (iii) surveys on trust, agency, and workload for teachers; and (iv) governance documents, such as consent forms and data-access documentation, since learners refuse to share all their data.

Procedure

Phase 1 develops constructs that can be measured at all four levels and establishes governance boundaries. Phase 2 carries out two rounds of design-based research in actual classrooms, where the teachers' reviewing, adapting, and overriding actions are recorded as primary data. Phase 3 makes a comparison of the adaptive and non-adaptive conditions for a time period sufficient to uncover the dependency on time demonstrated by meta-analyses. Phase 4 checks on the equity and ethics (access level, distributional impact, procedural accuracy) in relation to the adopted

principles. Phase 5 assesses teachers' competencies before and after a professional development module comparable to those which are known to address concerns and build trust.

Evaluation Dimensions

Table 2: Evaluation Dimensions and Candidate Indicators

Dimension	Indicator focus	Rationale
Cognitive achievement	Pre/post change in achievement; adaptive versus non-adaptive comparison	Established outcome of interest; achievement as reported outcome of adaptive instruction; ITS effects on test scores
Learner engagement and retention	Completion and engagement indices; retention rates	Optimised learning paths, engagement, and completion reported as AI/ML outcomes
Equity of access and outcome	Distribution of device, bandwidth, and literacy access; outcome variance across learner groups	Access inequality as a documented threat; risk of widening inequity gap
Teacher agency and trust	Frequency of recommendation acceptance, modification, override; trust measures	Teacher agency identified as key to trust
Ethical and procedural compliance	Consent coverage, data-access control, auditability, explainability documentation	Privacy protection, transparency, and auditability as core principles
Institutional sustainability	Continuity of implementation; cost and infrastructure feasibility	Infrastructure, cost, and readiness identified as critical barriers; technical, financial, and literacy barriers

Results

As this framework is conceptual in nature and not empirically tested, predictions are made in the form of directional hypotheses based on published standards, which the protocol being developed will be benchmarked against; considering the many definitions offered by the literature and lack of empirical research on ethics in educational AI, making predictions rather than performing an experiment would be counterproductive.

Hypothesis 1 - Integration maintains cognitive advantages. Integrating the four layers into a protocol may maintain the cognitive advantages of adaptive learning because the moderators of effect sizes in meta-analysis (adaptive source and target, time period, domain, level of learner) are the same variables that this framework controls.

Hypothesis 2 — Override capabilities boost recommendation acceptance. Teacher override capabilities are anticipated to increase acceptance levels relative to automated approaches, due to the increased trust associated with teacher capability to review, modify, and reject recommendations prior to their receipt by learners.

Proposition 3 — Governance-first deployment results in reduced outcome variability. Benchmarking access equity outcomes prior to implementation is likely to result in reduced outcome variability in order to mitigate the risk of increased inequities due to AI technology in education.

Proposition 4 — Teacher PD reduces reported burdens. Teacher professional development in the design of the program is expected to mitigate burdens of teacher workload and transparency, due to increased familiarity with AI-assisted assessment and avoidance of misconceptions and biases.

Reference magnitudes based on actual observations rather than predictions: average post-assessment scores increasing from 68.4 to 82.7 for 300 participants and 50 teachers, with higher completion and engagement, along with barriers associated with technical capability, teacher training, and infrastructure.

Discussion

Effect sizes are gathered from fig. 1, which summarizes findings from the independent meta-analyses discussed previously as 0.32 to 0.37 for ITS in higher education, 0.36 and 0.42 for overall and mathematics achievement in adaptive instruction, 0.66 for median of 50 controlled ITS studies, 0.70 for adaptive learning with AI, 0.86 for overall ITS impact size, and 0.924 for AI impact on academic achievement. Two important cautions need to be made, however. One, these are based on different research questions, comparative scenarios, and outcome measures, with 0.66 median being very sensitive to local vs. standardized measures. Two, none of the meta-analyses evaluates the sustainability impacts such as equity, teaching capacity, and organizational robustness. Arguments supporting this view can be stated in three points

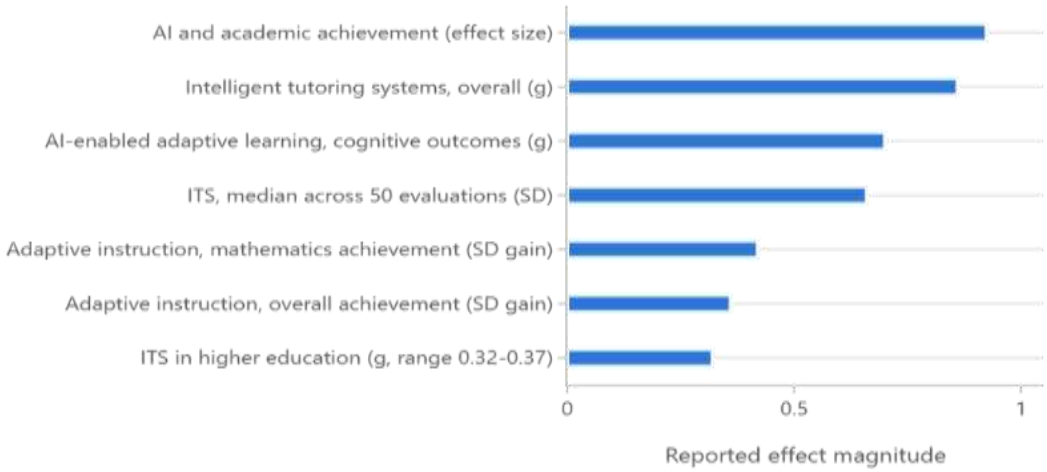


Fig. 1: Reported Effect Sizes for AI-Supported Personalised Learning Across Meta-Analyses

First, although there is a certain level of certainty in the cognitive outcomes, there is not much certainty in the broader claim that AI revolutionizes education; this is due to the positive effect on achievement and testing, the uncertain effect on motivation, knowledge, performance, problem-solving ability, and the decreasing effect in the latest research studies.

Second, the issue of integration is institutional and not technological because even though there was an AI-based approach in adaptive engines, the learning effects were not moderated by the algorithm, implying that improvement of the same will not yield any extra value; what is hindering integration and standardization is the gap between AI technology and existing educational frameworks.

Finally, equity is an aspect of design and not a post-hoc distribution issue because there exists the risk of increasing inequity with techno-solutionism while there are still unresolved issues about who the winner and loser groups are.

Educational Implications

For teachers and teaching. Teacher capacity is part of the system performance and not the user support cost since teacher agency is essential for trust. Therefore, institutions need to consider override capability as an essential procurement criterion and investment in professional development that helps reduce misconceptions and increase adoptability.

For institutions. Readiness of the institution technically, financially, and infrastructurally emerges again as a critical barrier. Institutions need to align adoption with the capacity of the infrastructure and measure sustainability in terms of continuity and cost feasibility.

For policymakers. The framework provides support for the requirements of auditing, explainability, and fairness as qualities that need to be evaluated in educational AI, along with school-based requirements for pedagogical appropriateness, children's rights, AI literacy, and teacher well-being, as well as the pedagogical support that is lacking in AI literacy.

For designers. As the class of algorithm does not affect the outcome, while fairness issues arise due to biased data and the training inputs, the focus needs to be shifted from algorithm innovation to data quality and explainability.

Equity Work. In light of the fact that inequalities in access to connectivity, devices, and knowledge about AI can create additional inequalities, access must be inclusive of resources and educator development for equity.

Conclusion and Future Scope

While it is clear from empirical studies that AI-based personalised learning is effective in boosting cognitive gains, having effect sizes ranging from 0.32 to 0.924 in various meta-studies, the proven success is not sufficient to ensure sustainable development of education. As it was argued in this paper, there is a certain gap between the proven effectiveness of personalised learning and sustainable development that could be addressed via the process of integration and governance of AI technologies. The proposed AIPL-SED model consists of four interrelated layers of learner modeling, adaptive sequencing, teacher orchestration, and sustainability governance, where the last one regulates the other three layers and provides feedback on the results of the outcomes. The following four directions

may serve as the subject for future investigation. Firstly, testing this theory via a mixed-methods approach that includes comparison of situations that are adaptive and non-adaptive in terms of achieving equity in access to resources. Secondly, longitudinal research in order to study the effect of equity because there is no such research available yet on the possibility of increasing disparities. Thirdly, indicators for the governance construct as the concepts of fairness, accountability, transparency, and ethics were not tested empirically as components of a classroom system.

References

Abulibdeh, A., Zaidan, E., & Abulibdeh, R. (2024). Navigating the confluence of artificial intelligence and education for sustainable development in the era of industry 4.0: Challenges, opportunities, and ethical dimensions. *Journal of cleaner production*, *437*, 140527. https://doi.org/10.1016/j.jclepro.2023.140527

Alamäki, A., Nyberg, C., Kimberley, A., & Salonen, A. O. (2024, March). Artificial intelligence literacy in sustainable development: A learning experiment in higher education. In *Frontiers in Education* (Vol. 9, p. 1343406). Frontiers Media SA. https://doi.org/10.3389/feduc.2024.1343406

Ayanwale, M. A., Adelana, O. P., & Odufuwa, T. T. (2024). Exploring STEAM teachers' trust in AI-based educational technologies: A structural equation modelling approach. *Discover education*, *3*(1), 44. https://doi.org/10.1007/s44217-024-00092-z

Adams, C., Pente, P., Lemermeyer, G., & Rockwell, G. (2023). Ethical principles for artificial intelligence in K-12 education. Computers and Education: Artificial Intelligence, 4, 100131. https://doi.org/10.1016/j.caeai.2023.100131

Ma, W., Adesope, O. O., Nesbit, J. C., & Liu, Q. (2014). Intelligent tutoring systems and learning outcomes: A meta-analysis. *Journal of educational psychology*, *106*(4), 901. https://doi.org/10.1037/a0037123

Ayeni, O. O., Al Hamad, N. M., Chisom, O. N., Osawaru, B., & Adewusi, O. E. (2024). AI in education: A review of personalized learning and educational technology. *GSC Advanced Research and Reviews*, *18*(2), 261-271. https://doi.org/10.30574/gscarr.2024.18.2.0062

Bhatta, R. P. (2025). AI in education for sustainable development: A comprehensive framework for equitable and quality learning. *Education*, *9*(10). https://doi.org/10.32628/cseit26121335

Bond, M., Khosravi, H., De Laat, M., Bergdahl, N., Negrea, V., Oxley, E., ... & Siemens, G. (2024). A meta systematic review of artificial intelligence in higher education: A call for increased ethics, collaboration, and rigour. *International journal of educational technology in higher education*, *21*(1), 4. https://doi.org/10.1186/s41239-023-00436-z

Bulathwela, S., Pérez-Ortiz, M., Holloway, C., Cukurova, M., & Shawe-Taylor, J. (2024). Artificial intelligence alone will not democratise education: On educational inequality, techno-solutionism and inclusive tools. *Sustainability*, *16*(2), 781. https://doi.org/10.3390/su16020781

Bouakaz, L., & Khalid, S. (2025, November). AI in education: A sociological exploration of technology in learning environments. In *Frontiers in Education* (Vol. 10, p. 1700876). Frontiers Media SA. https://doi.org/10.3389/feduc.2025.1700876

Chen, M. (2025). The impact of AI-assisted personalized learning on student academic achievement. *US-China Education Review A*, *15*(6), 441-450. https://doi.org/10.17265/2161-623x/2025.06.008

Crompton, H., & Burke, D. (2023). Artificial intelligence in higher education: The state of the field. *International journal of educational technology in higher education*, *20*(1), 22. https://doi.org/10.1186/s41239-023-00392-8

Colchester, K., Hagras, H., Alghazzawi, D., & Aldabbagh, G. (2017). A survey of artificial intelligence techniques employed for adaptive educational systems within e-learning platforms. *Journal of Artificial Intelligence and Soft Computing Research*, *7*(1), 47-64. https://doi.org/10.1515/jaiscr-2017-0004

Chan, C. K. Y. (2023). A comprehensive AI policy education framework for university teaching and learning. *International journal of educational technology in higher education*, *20*(1), 38. https://doi.org/10.1186/s41239-023-00408-3

Dong, L., Tang, X., & Wang, X. (2025). Examining the effect of artificial intelligence in relation to students' academic achievement: A meta-analysis. *Computers and Education: Artificial Intelligence*, *8*, 100400. https://doi.org/10.1016/j.caeai.2025.100400

Gligorea, I., Cioca, M., Oancea, R., Gorski, A. T., Gorski, H., & Tudorache, P. (2023). Adaptive learning using artificial intelligence in e-learning: A literature review. Education Sciences, 13(12), 1216. https://doi.org/10.3390/educsci13121216

George-Reyes, C. E., & López-Caudana, E. O. Boosting AI Literacy to Tackle Educational Inequality. In *Open Science and the Future of Education* (pp. 125-136). Routledge. https://doi.org/10.4324/9781003732945-9

Huang, X., Xu, W., & Liu, R. (2025). Effects of intelligent tutoring systems on educational outcomes: Evidence from a comprehensive analysis. *International Journal of Distance Education Technologies (IJDET)*, *23*(1), 1-25. https://doi.org/10.4018/ijdet.368420

Chen, H. (2024). The Ethical Challenges of Educational Artificial Intelligence and Coping Measures: A Discussion in the Context of the 2024 World Digital Education Conference. *Science Insights Education Frontiers*, *20*(2), 3263. https://doi.org/10.15354/sief.24.re339

Ifenthaler, D., Majumdar, R., Gorissen, P., Judge, M., Mishra, S., Raffaghelli, J., & Shimada, A. (2024). Artificial Intelligence in Education: Implications for Policymakers, Researchers, and Practitioners: D. Ifenthaler et al. *Technology, Knowledge and Learning*, *29*(4), 1693-1710. https://doi.org/10.1007/s10758-024-09747-0

Ilić, M., Mikić, V., Kopanja, L., & Vesin, B. (2023). Intelligent techniques in e-learning: a literature review: M. Ilić et al. *Artificial Intelligence Review*, *56*(12), 14907-14953. https://doi.org/10.1007/s10462-023-10508-1

Kulik, J. A., & Fletcher, J. D. (2016). Effectiveness of intelligent tutoring systems: A meta-analytic review. *Review of educational research*, *86*(1), 42-78. https://doi.org/10.3102/0034654315581420

Lin, C. C., Huang, A. Y., & Lu, O. H. (2023). Artificial intelligence in intelligent tutoring systems toward sustainable education: a systematic review. *Smart learning environments*, *10*(1), 41. https://doi.org/10.1186/s40561-023-00260-y

Lucas, M., Zhang, Y., Bem-Haja, P., & Vicente, P. N. (2024). The interplay between teachers' trust in artificial intelligence and digital competence. *Education and Information Technologies*, *29*(17), 22991-23010. https://doi.org/10.1007/s10639-024-12772-2

Memarian, B., & Doleck, T. (2023). Fairness, Accountability, Transparency, and Ethics (FATE) in Artificial Intelligence (AI) and higher education: A systematic review. *Computers and Education: Artificial Intelligence*, *5*, 100152. https://doi.org/10.1016/j.caeai.2023.100152

Nazaretsky, T., Ariely, M., Cukurova, M., & Alexandron, G. (2022). Teachers' trust in AI-powered educational technology and a professional development program to improve it. *British journal of educational technology*, *53*(4), 914-931. https://doi.org/10.1111/bjet.13232

Nguyen, A., Ngo, H. N., Hong, Y., Dang, B., & Nguyen, B. P. T. (2023). Ethical principles for artificial intelligence in education. *Education and information technologies*, *28*(4), 4221-4241. https://doi.org/10.1007/s10639-022-11316-w

Pedro, F., Subosa, M., Rivas, A., & Valverde, P. (2019). Artificial intelligence in education: Challenges and opportunities for sustainable development.

Prinsloo, P., & Khalil, M. (2024). The Democratisation of AI in, for and through Education: A Position Paper. *Ubiquity Proceedings*, *4*(1), 8-8. https://doi.org/10.5334/uproc.130

Roy, S. (2026). Democratizing Education with Artificial Intelligence: Bridging the Digital Divide. *Archives*. https://doi.org/10.25215/1105570053.17

Steenbergen-Hu, S., & Cooper, H. (2014). A meta-analysis of the effectiveness of intelligent tutoring systems on college students' academic learning. *Journal of educational psychology*, *106*(2), 331. https://doi.org/10.1037/a0034752

Sari, H. E., Tumanggor, B., & Efron, D. (2024). Improving educational outcomes through adaptive learning systems using AI. International Transactions on Artificial Intelligence, 3(1), 21-31. https://doi.org/10.33050/italic.v3i1.647

Viberg, O., Cukurova, M., Feldman-Maggor, Y. *et al.* What Explains Teachers' Trust in AI in Education Across Six Countries?. *Int J Artif Intell Educ* 35, 1288–1316 (2025). https://doi.org/10.1007/s40593-024-00433-x

Wang, X., Huang, R. T., Sommer, M., Pei, B., Shidfar, P., Rehman, M. S., ... & Martin, F. (2024). The efficacy of artificial intelligence-enabled adaptive learning systems from 2010 to 2022 on learner outcomes: A meta-analysis. *Journal of Educational Computing Research*, *62*(6), 1348-1383. https://doi.org/10.1177/07356331241240459

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education–where are the educators?. *International journal of educational technology in higher education*, *16*(1), 39. https://doi.org/10.1186/s41239-019-0171-0

Zawacki-Richter, O., Bai, J. Y., Lee, K., Slagter van Tryon, P. J., & Prinsloo, P. (2024). New advances in artificial intelligence applications in higher education?. *International Journal of Educational Technology in Higher Education*, *21*(1), 32. https://doi.org/10.1186/s41239-024-00464-3