International Journal of Computational Research in Science and Technology
E-ISSN: 3108-0871, Volume 2 Issue 5
Sep-Oct-2026, PP 01-08

Artificial Intelligence In Education And Healthcare: A Comparative Review Of Applications, Shared Techniques And Responsible Adoption

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Abstract—Education and healthcare are two sectors with enormous social impact, chronic shortages of skilled professionals and large unmet demand, particularly in developing countries. Artificial Intelligence is being applied in both to personalize services, automate routine work and support expert decisions. This paper reviews AI in education and healthcare side by side, highlighting both their distinct applications and the techniques they share. In education, the review covers learning analytics, adaptive learning and tutoring, automated assessment and generative AI assistants for students and teachers. In healthcare, it covers diagnostic support from images and records, remote monitoring and conversational assistants. Shared foundations, including predictive modelling of individuals, recommendation of personalized next steps, natural language processing and human-in-the-loop decision support, are analysed. Cross-sector concerns of privacy of sensitive personal data, bias, transparency, over-reliance and the digital divide are discussed with reference to international guidance. A unified five-layer architecture for personalized AI services in both domains is proposed, together with research gaps, objectives and a comparison table. The review concludes that lessons learned in one sector can accelerate responsible adoption in the other.

Index Terms—Artificial intelligence, education, healthcare, personalization, learning analytics, clinical decision support, generative AI, ethics

I. Introduction

A teacher responsible for sixty students and a doctor seeing a hundred patients a day face a similar problem: they cannot give each person the individual attention they need. In both cases, AI promises to extend expert capacity by analysing individual data, personalizing guidance and taking over repetitive tasks.

Research on AI in education and AI in healthcare has largely developed separately. Zawacki-Richter *et al.* [1] reviewed AI in higher education and found that most studies came from computer science with little involvement of educators, while Rajpurkar *et al.* [2] and Yu *et al.* [3] reviewed AI in medicine and highlighted the gap between laboratory accuracy and clinical impact. Both bodies of work point to similar opportunities and risks.

This paper reviews AI in both sectors together, identifies shared techniques and challenges, and proposes a unified architecture for personalized AI services.

II. Background and Related Work

2.1 Parallel Applications

Fig. 1 places applications from both sectors side by side, showing that each sector uses AI to assess the individual, personalize interventions, support professionals and automate administration.

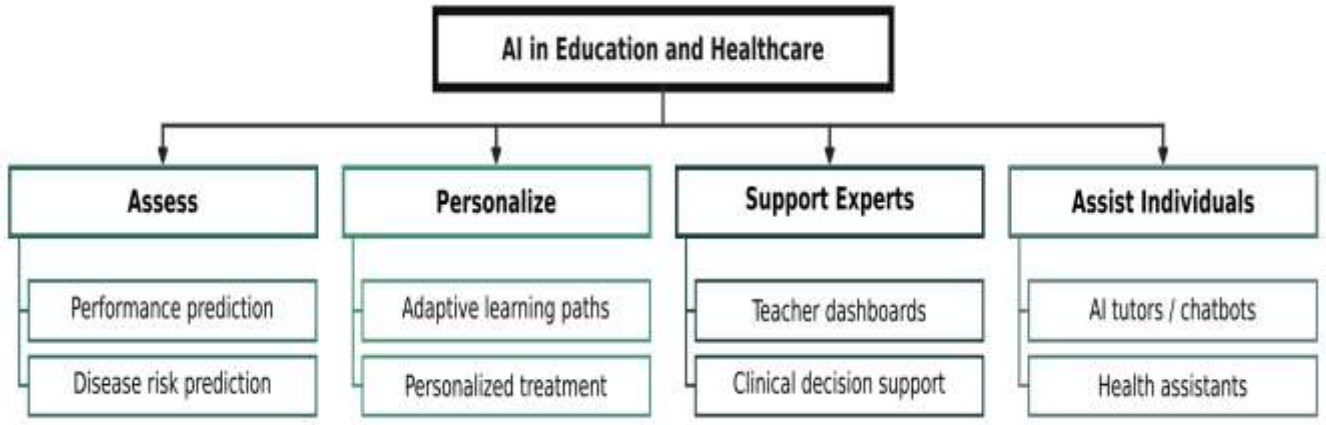


Fig. 1. Parallel AI applications in education and healthcare.

2.2 Shared Techniques

Both sectors predict outcomes for individuals (exam performance or disease risk), recommend next steps (learning resources or treatments), process natural language (essays or clinical notes) and increasingly use large language models as assistants.

2.3 Review of Related Studies

Education. Romero and Ventura [4] reviewed educational data mining, including prediction of student performance and detection of undesirable behaviour. Corbett and Anderson [5] introduced knowledge tracing, and Piech *et al.* [6] extended it with deep learning to model what a student knows. Kasneci *et al.* [7] discussed the opportunities and challenges of large language models for education, including personalized explanations and the risk of plagiarism and over-reliance. UNESCO [8] published guidance calling for human-centred, age-appropriate use of generative AI in schools.

Healthcare. Topol [9] argued that AI could restore the human connection in medicine by relieving clinicians of routine tasks. Esteva *et al.* [10] demonstrated dermatologist-level skin-lesion classification, and Rajkomar *et al.* [11] predicted outcomes from complete health records. Rajpurkar *et al.* [2] reviewed recent progress and stressed prospective validation.

Cross-sector risks. Obermeyer *et al.* [12] showed how a healthcare algorithm encoded racial bias, and Baker and Hawn [13] documented similar algorithmic bias in education, illustrating a shared risk. Table I summarizes these works.

TABLE I Summary of Literature Survey

Sr. No.	Ref.	Year	Methodology	Findings	Research Gap
1	[4]	2010	Review of educational data mining	Mapped EDM tasks	Pre-LLM era
2	[6]	2015	Deep knowledge tracing	Better mastery prediction	Opaque model
3	[11]	2018	Deep learning on health records	Accurate outcome prediction	US hospitals
4	[1]	2019	Review of AI in higher education	Few educators involved in research	Higher education only
5	[9]	2019	Review of AI in medicine	Human–AI partnership vision	Limited outcome evidence
6	[12]	2019	Healthcare algorithm bias audit	Revealed racial bias	Single algorithm
7	[13]	2022	Algorithmic bias in education	Documented unequal performance	Mostly US studies
8	[7]	2023	LLMs for education	Opportunities and risks identified	Position paper

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III. Research Gap and Objectives

3.1 Identified Research Gaps

G1: Few studies compare AI adoption experiences across sectors to share lessons.

G2: Evidence of long-term learning gains or health outcomes from AI is limited.

G3: Both sectors handle sensitive data about minors or patients with inconsistent protections.

G4: Teachers and clinicians receive little training in using and questioning AI tools.

G5: Digital divides limit access in rural areas in both sectors.

3.2 Objectives of the Review

O1: To review AI applications in education and in healthcare.

O2: To identify techniques and design patterns shared by both sectors.

O3: To propose a unified architecture for personalized AI services.

O4: To compare applications, benefits and risks across sectors.

O5: To recommend responsible adoption practices.

IV. Design of the Proposed System

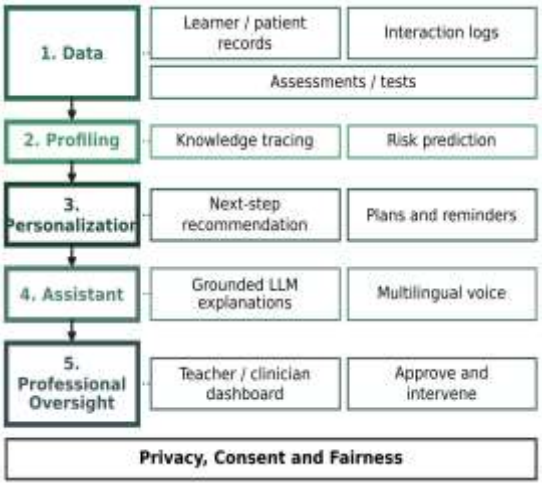


Fig. 2 presents a unified architecture applicable to both a learning platform and a health service.

Fig. 2. Unified architecture for personalized AI services in education and healthcare.

4.1 Data Layer

Learner or patient records, interaction logs, assessments or tests and, with consent, sensor data are collected securely.

4.2 Profiling Layer

Models estimate the current state of each individual: knowledge mastery for a student, risk profile for a patient.

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4.3 Personalization Layer

Recommendation and planning modules suggest the next lesson, practice task, lifestyle change or follow-up test.

4.4 Assistant Layer

A language-model assistant explains concepts or health information in simple language, grounded in curated content.

4.5 Professional Oversight Layer

Teachers and clinicians review dashboards, approve or adjust recommendations and intervene when needed.

4.6 Methodology

Fig. 3 shows the common workflow. In knowledge tracing, the probability that a learner has mastered a skill is updated after each answer; in risk prediction, a patient's risk is updated after each test. Both can be written as a Bayesian update

$$P(s \mid e) = P(e \mid s) \cdot P(s) / P(e) \qquad (1)$$

where s is the hidden state (mastery or disease) and e the new evidence (an answer or a test result).

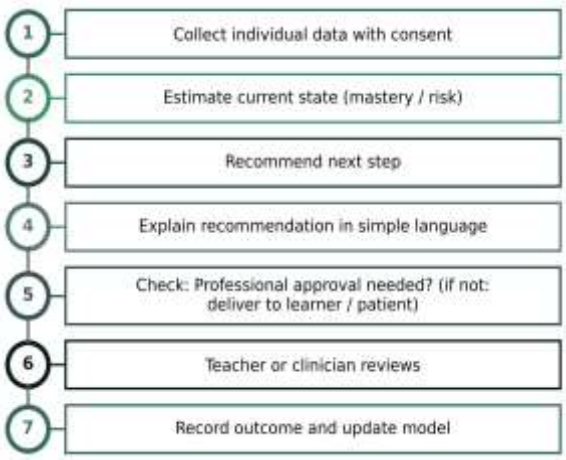


Fig. 3. Common workflow for personalized AI services.

Evaluation includes predictive accuracy and, more importantly, measured improvements in learning or health outcomes and fairness across groups.

V. Discussion and Comparison

Table II compares AI use across the two sectors. Healthcare faces stricter regulation and higher stakes per decision, while education deals with very large populations and minors, but both require explainability and human oversight.

TABLE II Comparison of AI Use in Education and Healthcare

Aspect	Education	Healthcare
Main goal	Better learning outcomes	Better health outcomes
Typical data	Grades, logs, essays	Images, records, notes
Stakes per decision	Moderate	High
Regulation	Emerging guidance	Strict, device rules
Key risk	Over-reliance, bias	Unsafe advice, bias

VI. Challenges and Future Directions

Table III summarizes cross-sector challenges. Future work includes shared ethical frameworks, privacy-preserving analytics, AI literacy training for teachers and clinicians, and offline multilingual tools for rural schools and clinics.

Challenge	Mitigation
Sensitive data	Consent, encryption, minimal collection
Bias	Subgroup evaluation in both sectors
Over-reliance	Human oversight; AI literacy
Digital divide	Offline, low-cost, multilingual tools
Weak outcome evidence	Controlled trials and long-term studies

TABLE III Challenges and Mitigation

VII. Conclusions

AI in education and AI in healthcare are more alike than they first appear: both aim to understand individuals, personalize support and extend scarce expertise. The reviewed literature shows strong technical progress in each sector and the same recurring risks of bias, privacy breaches and over-reliance. A unified, human-supervised architecture and shared lessons across sectors can help both adopt AI responsibly and equitably.

7.1 Acknowledgment

The authors express their sincere gratitude to the Department of Artificial Intelligence and Data Science, Jaihind College of Engineering, Pune, for providing the facilities, guidance and encouragement needed to carry out this work. The authors also thank the faculty members and colleagues whose valuable suggestions helped improve the quality of this review.

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