Artificial Intelligence for Adaptive Learning in Health Professions Education: A Scoping Review of Emerging Innovations

Serkan Toy¹, C Hebert¹, Maedot Haymete¹, Scott Pappada², Levent Çetinkaya³, Kavya Iyer⁴, Brock Mutcheson¹, Cozette Comer⁵, Jackson Hoch⁵, Jed Gonzalo¹

1VTCSOM; ²UToledo; ³Canakkale Onsekiz Mart University; ⁴VT, TBMH; ⁵Evidence Synthesis Services, University Libraries at Virginia Tech







INTRODUCTION

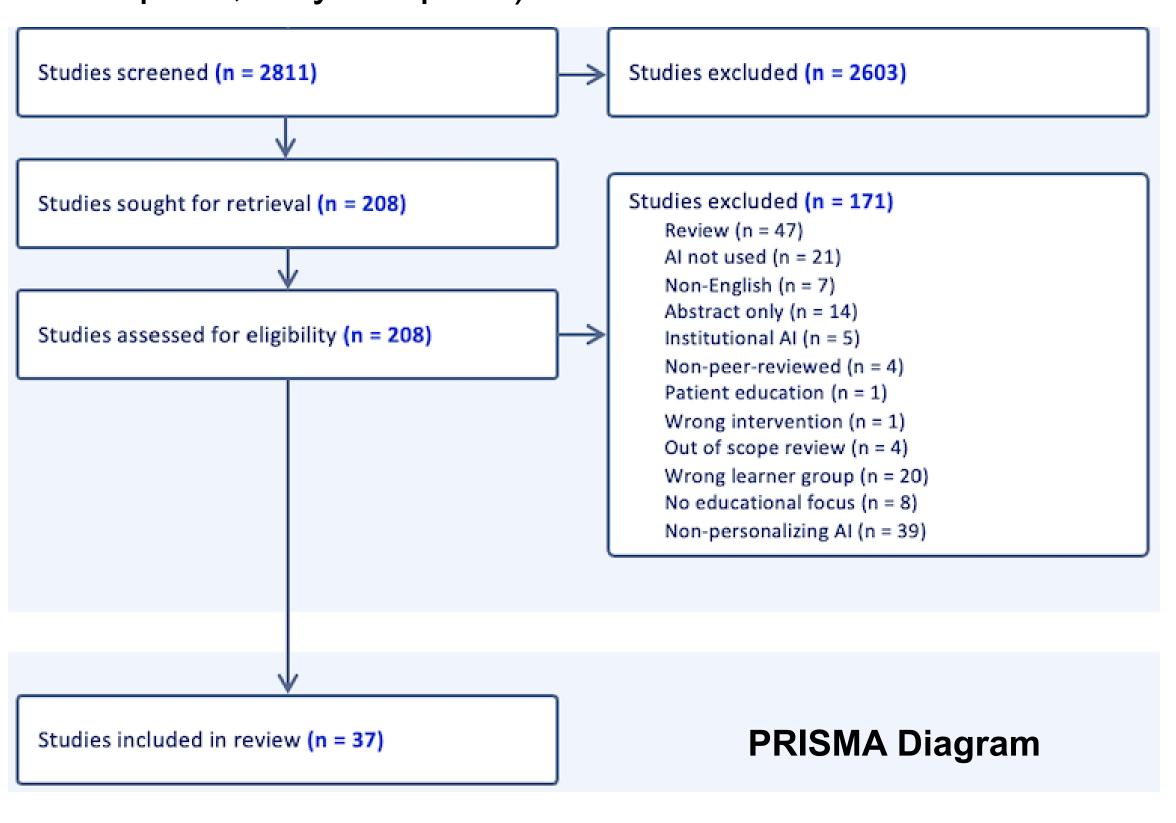
- Artificial intelligence (AI) is increasingly explored for personalized/adaptive learning in health professions education.
- Adaptive learning systems align well with competencybased education by tailoring instruction, feedback, and learner pathways.
- Yet, many implementations remain performance-driven, rather than learner-centered [1-3].
- This review synthesizes evidence on how AI-enabled systems support adaptivity and what pedagogical implications emerge.

Objectives

- Map existing Al-enabled adaptive learning systems in health professions education.
- Classify systems by degree of adaptivity.
- Examine alignment with educational theory and learner-centered design.

MATERIALS & METHODS

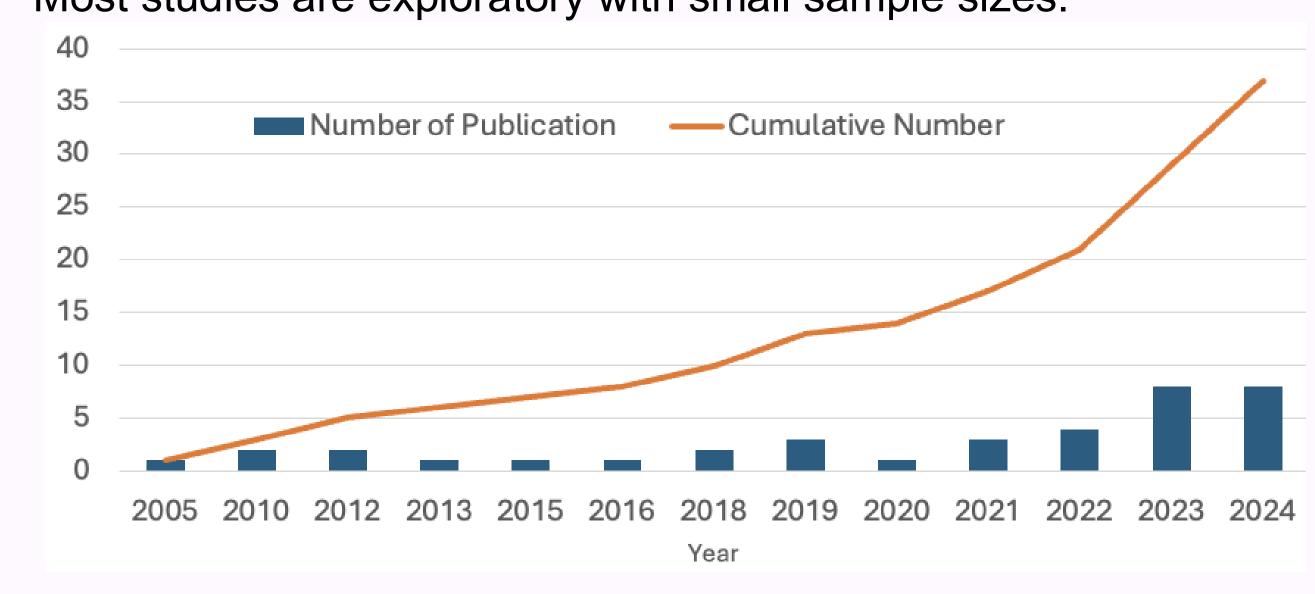
- Scoping review (Joanna Briggs Institute methodology [4]).
- Search strategy: Developed with two and run by one evidence synthesis librarian(s).
- Screening: 7 reviewers; in duplicate, with a third reviewer resolving disagreements.
- Decision tree: Used to ensure consistency in inclusion/exclusion during full-text review.
- Data extraction: Al techniques, learner inputs, personalization strategies, timing of adaptation, and evaluation outcomes.
- Classification: Tiered framework (foundational, semi-adaptive, fully adaptive).



RESULTS

Study Characteristics

- 37 studies included (2005–2024).
- Growth in publications accelerated after 2020. (see trend chart)
- Most studies are exploratory with small sample sizes.



Al Techniques

- Supervised ML (54%)
- Natural Language Processing (35%)
- Generative AI (8%)

Tiered Classification of Al-Enabled Adaptive Systems

Foundational (n=11)
Static personalization
•Pre-programmed rules or branching logic
•One-size-fits-most pathways
•Minimal learner input

Semi-Adaptive (n=8)

Limited real-time adjustment

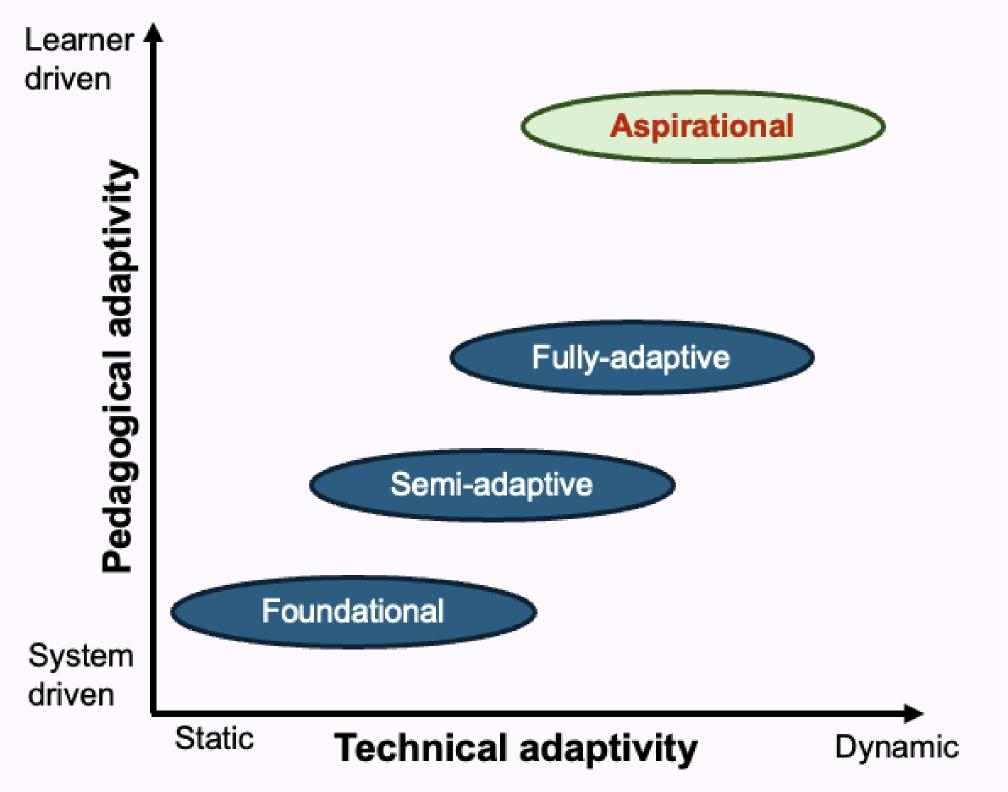
•Adapts to learner
responses/choices
•Some personalization, not

Some personalization, not continuousNarrow scope of feedback

Fully Adaptive (n=18)
Continuous personalization
•Uses multimodal learner data
(physiology, NLP, etc.)
•Real-time, dynamic feedback
•Enables more individualized
learning

Higher technical adaptivity increases the potential, but not the realization of, pedagogical adaptivity.

Bridging Technical & Pedagogical Adaptivity



Most Al-enabled systems show technical adaptivity through automation, modeling, or feedback. However, few include pedagogical adaptivity features like reflection, formative feedback, or learner agency.

RESULTS (CONT.)

Gaps Identified

- Evaluation focus: Mostly task accuracy & completion time; rarely reflection, retention, or behavior change.
- Learner role: Typically passive, limited goal-setting, reflection, or agency.
- Feedback: Often static/system-driven, not fostering self-regulated learning or metacognition.
- Theoretical grounding: Few systems are anchored in educational theory.

CONCLUSION

- Al systems demonstrate technical sophistication but limited pedagogical adaptivity.
- Most designs emphasize automation and performance, underutilizing Al's potential to support reflection, metacognition, and learner agency.
- The tiered framework reveals that higher technical adaptivity increases potential, but not necessarily achievement, of pedagogical adaptivity.

To advance adaptive learning in higher education:

- Integrate formative feedback aligned with self-regulated learning.
- Foster metacognition and learner agency through learner-centered design.
- Align Al innovation with educational frameworks, not just technical capacity.

Future direction: Al for education should move beyond automation to enable deep learning, reflection, and adaptive expertise.

Al's promise lies not in automation alone, but in supporting rich, learner-centered pedagogies.

REFERENCES & ACKNOWLEDGEMENTS

- [1] Feigerlova E et al. (2025). BMC Med Educ 25(1):129. https://doi.org/10.1186/s12909-025-06719-5
- [2] Gordon M et al. (2024). Med Teach 46(4):446-470. https://doi.org/10.1080/0142159X.2024.2314198
- [3] Kang N et al. (2025). J Nurs Manag 2025(1):6689213. https://doi.org/10.1155/jonm/6689213
- [4] Peters MDJ et al. (2020). JBI Evid Synth 18(10):2119-2126. https://doi.org/10.11124/JBIES-20-00167