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The impact of Artificial Intelligence Tools on E-Learning outcomes in higher education

Sibonangaye Dick Nkalanga[1] & Mohammed Xolile Ntshangase[1]

[1] University of Limpopo, South Africa.

ABSTRACT

The incorporation of artificial intelligence (AI) in higher education has essentially transformed the kind of learning paces found in e-learning environments. Despite this, very little thorough and comprehensive research has been done on the impact of these technologies on students' educational results. This study questions how student learning can be either helped by or hindered through the use of AI tools, which AI tools are the most efficient in different contexts, and what the challenges and opportunities raised by the introduction of these tools are. Building on a systematic review, literature review, and qualitative analysis, this paper analysed 31 peer-reviewed articles published between 2020 and 2026 as well as twelve visits to higher education institutions. Besides semi-structured document analysis, this study combined stakeholder engagement to portray the implementation experiences in diverse environments. The findings reveal that AI, AI-powered adaptive learning platforms, intelligent tutoring systems, and automated assessment tools have induced significant improvements in student performance indicators, with grades rising between 8% and 15% in different disciplines. Nevertheless, the study also reveals that the research community is facing some issues concerning academic integrity, the widening of the digital divide, the danger of over-dependence on AI and the challenges faced in faculty readiness. The article provides scientifically supported information about the use of AI in higher education while emphasising the vital importance of human-AI collaboration. It carries educational ramifications for teachers, school leaders, and policymakers, along with suggestions for the ethical use of AI in e-learning environments.

Keywords: Artificial Intelligence, E-Learning, Learning Outcomes, Educational Technology, Online Education.

INTRODUCTION

Digitisation in higher education has changed radically, mostly during the past few years when COVID-19 was a big part in the increased use of educational technologies. In fact, the switch to virtual and hybrid learning models was the reason for putting artificial intelligence (AI) tools in the spotlight to completely change the teaching and learning methods. Studies show that many AI tools have become a part of education, for example, intelligent tutoring systems that tailor one-on-one learning strategies or natural language processing tools that help instructors provide immediate feedback.[1]

[1] Olaf Zawacki-Richter et al., "Systematic Review of Research on Artificial Intelligence Applications in Higher Education – Where Are the Educators?," *International Journal of Educational Technology in Higher Education* 16, no. 1 (December 28, 2019): 39,

CORRESPONDENCE – Sibonangaye Dick Nkalanga **Email**: sibonangaye.nkalanga@ul.ac.za
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In combination with its many positive aspects, AI comes with its associated problems. From a student's point of view, AI-powered devices can provide them with tailored study materials, offer prompt responses to students' queries, and even extend a hand whenever the student needs it, cutting across time and space limitations.[2] About the teaching staff, this technology could unlock ways of resolving challenging issues like instruction differentiation, instant response to student assessments and detection of possible drop-outs.[3] For the higher education sector altogether, AI might help institutions to raise the level of quality education they offer while at the same time supervising student retention and performance data.[4]

Moreover, despite the rapid uptake, a rigorous and exhaustive examination of the actual influence of AI tools on learning outcomes is still lacking and is quite patchy across various disciplines, settings, and modes of implementation. While commercial enterprises promote it spectacularly, dependable academic research is scarce. One of the significant concerns is whether students genuinely achieve better learning outcomes in an AI-facilitated e-learning environment, or whether AI just masquerades as a personalised learning tool while, in fact, it limits students' deep cognitive engagement. Besides that, the primary question remains as to how different sorts of AI technologies will impact different learning domains, for example, knowledge acquisition versus critical thinking. What are the negative consequences of becoming more dependent on AI-based learning?

This article seeks to understand the influence of AI tools on e-learning maturity outcomes in higher education by conducting a systematic review of recent scholarly articles, implementation case studies and emerging trends. It also identifies three major research questions that are the core of the study:

1. How do AI tools in e-learning settings affect student learning outcomes when these outcomes are measured through parameters like academic achievement, student engagement, and the quality of their experience?
2. Which kinds of AI tools are most suitable or effective for certain teaching scenarios, subject areas and student populations?
3. What are the challenges and opportunities brought about by AI integration, and how can institutional implementation be done in ways that maximise benefits and minimise risks?
   On the other hand, the research also explores the direct implications for education, both in terms of policy as well as practice.

Most campuses have installed the latest AI tools that students actively use in their education; That's why deciding based on data has become a must. This work contributes to the discussion around educational technology by summarizing the current academic literature, pointing out effective methods, and suggesting ways forward for AI-integrated e-learning, including research methods.

LITERATURE REVIEW

The review of literature summarises the recent studies on AI-assisted learning in higher education that explored different AI tools and their effects on learning outcomes. Among AI tools in education, adaptive learning platforms have attracted most of the research attention. In their systematic review, Martin et al. pointed out that these platforms largely lead to the improvement of learning outcomes, especially in STEM fields.[5] On average, students using adaptive learning platforms scored 8-12%

https://doi.org/10.1186/s41239-019-0171-0; Wayne Holmes, Maya Bialik, and Charles Fadel, *Artificial Intelligence in Education Promises and Implications for Teaching and Learning* (Center for Curriculum Redesign, 2019).

[2] Rose Luckin and Wayne Holmes, "Intelligence Unleashed: An Argument for AI in Education," 2016.

[3] Ryan Shaun Baker and Paul Salvador Inventado, "Educational Data Mining and Learning Analytics," in *Learning Analytics* (New York, NY: Springer New York, 2014), 61–75, https://doi.org/10.1007/978-1-4614-3305-7_4.

[4] Xieling Chen et al., "Past, Present, and Future of Smart Learning: A Topic-Based Bibliometric Analysis," *International Journal of Educational Technology in Higher Education* 18, no. 1 (2021): 2.

[5] Florence Martin et al., "Systematic Review of Adaptive Learning Research Designs, Context, Strategies, and Technologies from 2009 to 2018," *Educational Technology Research and Development* 68, no. 4 (August 15, 2020): 1903–29, https://doi.org/10.1007/s11423-020-09793-2.

higher in tests than students taught through traditional methods; parental knowledge brought the largest gains. Intelligent tutoring systems (ITS) are also among the most effective educational tools. For example, a meta-analytical study of 50 different studies by Ma et al. revealed that ITS-related learning had an average effect size of 0. 42 standard deviations greater, especially in the teaching of math and science.[6]

VanLehn argued that the effectiveness of a well-designed ITS could be comparable to that of human tutoring.[7] But ITS is ahead of humans only when it comes to teaching procedural skills. It is fundamentally challenging for ITS to assist in higher-order thinking and complex problem-solving that necessitate human judgment. Because of this, IITs at present has only a limited presence in this sphere. Automated writing assessment (AWA) tools could be helpful when it comes to partial replacement and feedback for teachers. Using these tools, students not only enhance their writing skills but are also stimulated to continue through the provision of immediate formative feedback.[8] Still, this is accompanied by a risk that students are influenced by these tools to produce formulaic pieces that fit the algorithm rather than authentic and effective communication.[9] Large language models, aka generative AI, are viewed as the breakthrough that has changed the game, raising a lot of concerns about academic dishonesty, authenticity in assessment, and the development of critical thinking.[10]

Even though AI-generated writing is still hard to identify, some educators consider this a challenge and therefore focus more on creative activities that AI cannot easily replicate.[11] AI-learning analytics platforms have drawn great attention these days because these systems can identify students at risk with as much as 70-85% forecasting accuracy of course graduation.[12] The use of these analytics-based systems and timely interventions led to a rise in student success rates by 12-18%.[13] However, the level of success depends on the students' self-regulated learning capabilities, which have to be encouraged and not just identified for intervention, with major privacy and ethical issues.[14] Even though 68% of them agreed that AI would bring about positive changes, the faculty research reveals a combination of both excitement and worry. Nazaretsky et al. revealed that a large percentage of these faculty members were scared of cheating possibilities (64%), fairness (57%), and how AI could help in the development of deep-thinking skills in students (49%).[15] The level of faculty AI awareness and preparedness varies widely; Because of this, a holistic faculty training program that concentrates not only on the pedagogical integration of AI but also on a critical assessment of the advantages and disadvantages of AI tools is highly desirable. Currently, there are a number of papers that highlight how AI-assisted learning could greatly improve student learning outcomes. Still, the real impact depends greatly on the quality of implementation, pedagogical integration, equity considerations, and

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[6] Wenting Ma et al., "Intelligent Tutoring Systems and Learning Outcomes: A Meta-Analysis.," *Journal of Educational Psychology* 106, no. 4 (2014): 901.

[7] Kurt VanLEHN, "The Relative Effectiveness of Human Tutoring, Intelligent Tutoring Systems, and Other Tutoring Systems," *Educational Psychologist* 46, no. 4 (October 2011): 197–221, https://doi.org/10.1080/00461520.2011.611369.

[8] Joshua Wilson and Amanda Czik, "Automated Essay Evaluation Software in English Language Arts Classrooms: Effects on Teacher Feedback, Student Motivation, and Writing Quality," *Computers & Education* 100 (September 2016): 94–109, https://doi.org/10.1016/j.compedu.2016.05.004.

[9] Mark D. Shermis and Jill Burstein, eds., *Handbook of Automated Essay Evaluation* (Routledge, 2013), https://doi.org/10.4324/9780203122761.

[10] M. Sullivan, A. Kelly, and P. McLaughlan, "ChatGPT in Higher Education: Considerations for Academic Integrity and Student Learning," *Journal of Applied Learning & Teaching* 6, no. 1 (March 21, 2023), https://doi.org/10.37074/jalt.2023.6.1.17.

[11] Mike Perkins et al., "Detection of GPT-4 Generated Text in Higher Education: Combining Academic Judgement and Software to Identify Generative AI Tool Misuse," *Journal of Academic Ethics* 22, no. 1 (2024): 89–113.

[12] Olga Viberg et al., "The Current Landscape of Learning Analytics in Higher Education," *Computers in Human Behavior* 89 (December 2018): 98–110, https://doi.org/10.1016/j.chb.2018.07.027.

[13] Baker and Inventado, "Educational Data Mining and Learning Analytics"; Dirk Ifenthaler and Jane Yin-Kim Yau, "Utilising Learning Analytics to Support Study Success in Higher Education: A Systematic Review," *Educational Technology Research and Development* 68, no. 4 (August 12, 2020): 1961–90, https://doi.org/10.1007/s11423-020-09788-z.

[14] Ido Roll and Philip H. Winne, "Understanding, Evaluating, and Supporting Self-Regulated Learning Using Learning Analytics," *Journal of Learning Analytics* 2, no. 1 (July 15, 2015): 7–12, https://doi.org/10.18608/jla.2015.21.2; Hassan Khosravi et al., "Explainable Artificial Intelligence in Education," *Computers and Education: Artificial Intelligence* 3 (2022): 100074, https://doi.org/10.1016/j.caeai.2022.100074.

[15] Tanya Nazaretsky et al., "Teachers' Trust in AI-powered Educational Technology and a Professional Development Program to Improve It," *British Journal of Educational Technology* 53, no. 4 (July 9, 2022): 914–31, https://doi.org/10.1111/bjet.13232.

ongoing assessment. And, the main concerns highlighted in the literature are the lack of longitudinal studies focusing on long-term retention, very few investigations on the differential impacts on various student populations, and very limited knowledge of the best combinations of different AI tools and teaching methods.

THEORETICAL FRAMEWORK

This paper presents a theoretical structure that blends different perspectives to examine the major impact of AI on e-learning education. The structure also explains, among other things, that technology adoption, learning changes, and outcome achievements are complex problems in that technology facilitation or affordance, pedagogical approaches, learner characteristics, and contextual elements are brought together.[16] The Technology Acceptance Model (TAM), which was initially developed by Davis and later revised by Venkatesh and his co-authors, gives the main insights on technology adoption.[17] Based on TAM, behind the adoption of technology, users' perception of the usefulness of the system and the ease of use of the system are the two main deciding factors.[18] The use of this model in AI and e-learning shows that learning tools should be not only very useful for learners but also very user-friendly, so even first-time users do not face any challenges.

Besides, the model extensions have brought in variables from the outside world, like system design quality, user training, and staff support as factors influencing user perceptions and adoption; social influence and facilitating conditions in educational institutions have been made explicit, and technology adoption is also being emphasized.[19]

Self-regulated learning (SRL) theory has been the point to which reference is often made when debating the effect of AI on learner autonomy and metacognitive skill development. The SRL model devised by Zimmerman identifies setting goals, self-monitoring, and self-regulation of cognitive strategies, as well as motivation management, as the major features of the learning process.[20] AI learning platforms with the capability to monitor learners' progress, provide goal-setting guidance, and allow reflection and adaptation are significant sources for SRL development.[21] On the other hand, technologies used for learning that turn students into passive knowledge recipients, as well as those that are always solving their problems, can, in fact, have a negative psychological impact on the accumulation of self-regulatory skills, which, among other things, are crucial for lifelong learning.[22] While the argument is that help is advisable, overhelping could be detrimental, and that's the tricky part in the design and use of AI tools.

The Constructivist Learning Theory, as elucidated by Bada and Olusegun, stresses that students deeply internalize and construct knowledge when they are cognitively (actively) engaged in the learning process, whereas a method of teaching that prompts students to receive the information passively is labelled as COGNITION/RECEPTION.[23] AI can be used to interact with concepts, support gradual exploration, and serve as a persuasive tool within the student's zone of proximal development for students to internalize knowledge. The writer contrasts the ability of AI to deliver the right answers quickly with the students discovering the answers through experience, struggle, and their own

[16] A Bozkurt et al., "A Global Outlook to the Interruption of Education Due to COVID-19 Pandemic: Navigating in a Time of Uncertainty and Crisis," *Asian Journal of Distance Education* 15, no. 1 (2021): 1–126.
[17] Fred D. Davis, "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology," *MIS Quarterly* 13, no. 3 (September 1, 1989): 319–40, https://doi.org/10.2307/249008.
[18] Andrina Granić and Nikola Marangunić, "Technology Acceptance Model in Educational Context: A Systematic Literature Review," *British Journal of Educational Technology* 50, no. 5 (September 9, 2019): 2572–93, https://doi.org/10.1111/bjet.12864.
[19] Mostafa Al-Emran, Vitaliy Mezhuyev, and Adzhar Kamaludin, "Towards a Conceptual Model for Examining the Impact of Knowledge Management Factors on Mobile Learning Acceptance," *Technology in Society* 61 (May 2020): 101247, https://doi.org/10.1016/j.techsoc.2020.101247.
[20] Barry J. Zimmerman, "Becoming a Self-Regulated Learner: An Overview," *Theory Into Practice* 41, no. 2 (May 2002): 64–70, https://doi.org/10.1207/s15430421tip4102_2.
[21] Ernesto Panadero, "A Review of Self-Regulated Learning: Six Models and Four Directions for Research," *Frontiers in Psychology* 8 (April 28, 2017), https://doi.org/10.3389/fpsyg.2017.00422.
[22] Roll and Winne, "Understanding, Evaluating, and Supporting Self-Regulated Learning Using Learning Analytics."
[23] Steve Olusegun Bada and Steve Olusegun, "Constructivism Learning Theory: A Paradigm for Teaching and Learning," *Journal of Research & Method in Education* 5, no. 6 (2015): 66–70.

independent problem-solving processes.[24] This means that AI can be considered a tutor who adapts its teaching style to the learner's exploratory behaviour, level of difficulty, as well as independent problem-solving abilities and thus provides learning opportunities of various kinds if the sandbox is the learning environment.

Personalised learning theory also supports the previous theme by focusing on tailoring the teaching methods to the individual differences of learners such as their prior knowledge, learning styles, motivational profiles, and developmental readiness.[25] AI tools enable personalisation on a grand scale that was virtually unimaginable before. However, for effective personalisation, it is imperative that one has a very nuanced understanding of what, when, and how to personalize.[26] Personalizing at a large scale is not merely about modifications in task difficulty levels but rather changes in the way content is delivered, the types of learning activities, forms of feedback, and variations in pacing flexibility. This entire process of personalisation using AI serves as the theoretical base for how AI can really be a great help to learning.

METHODOLOGY

This study utilised a mixed-methods approach that combined a comprehensive review of the literature with a qualitative examination of institutional AI implementations in e-learning contexts. The research design features a review of the latest academic publications along with an in-depth analysis of stakeholder experiences, problems of implementation, and environmental factors affecting AI effectiveness.

Research Approach

The research was carried out within an interpretive way of thinking that regards the influence of AI in education not merely as changes that can be measured but also through the factors which provide the context for the changes and which affect how the changes are made and experienced. The setup is based on the understanding that the success of educational technology cannot be illustrated by simple cause-and-effect models, as there is a major role for the interaction element of technology, pedagogy, and the student setting.[27] To have a wider understanding of the research problem with the help of different types of data and methods, the study used a mixed-methods design. The term "mixed-methods" is appropriate because of the simultaneous use of quantitative descriptive synthesis (numerical outcome data from 31 studies) and qualitative thematic analysis (documentary evidence from 12 institutions), which altogether create the two methodological strands of a sequential explanatory mixed-methods design.[28] As a result, this approach enhances the reliability and offers a more comprehensive understanding of the research than either quantitative or qualitative methods alone. The study used a sequential explanatory model. In this model, the quantitative analysis of the outcomes of the literature was done first, and then the qualitative study of the implementation narratives was done, which explained the patterns observed in the literature. So the quantitative phase: finding results gave the direction for the qualitative phase, and the qualitative data provided the depth and context which were necessary for the interpretation of the quantitative findings.

[24] Paul A. Kirschner, John Sweller, and Richard E. Clark, "Why Minimal Guidance During Instruction Does Not Work: An Analysis of the Failure of Constructivist, Discovery, Problem-Based, Experiential, and Inquiry-Based Teaching," *Educational Psychologist* 41, no. 2 (June 2006): 75–86, https://doi.org/10.1207/s15326985ep4102_1.

[25] Vaughan Prain et al., "Personalised Learning: Lessons to Be Learnt," *British Educational Research Journal* 39, no. 4 (August 25, 2013): 654–76, https://doi.org/10.1080/01411926.2012.669747.

[26] Candace Walkington and Matthew L. Bernacki, "Appraising Research on Personalized Learning: Definitions, Theoretical Alignment, Advancements, and Future Directions," *Journal of Research on Technology in Education* 52, no. 3 (July 2, 2020): 235–52, https://doi.org/10.1080/15391523.2020.1747757.

[27] J. W Creswell and C. N Poth, *Qualitative Inquiry and Research Design: Choosing among Five Approaches*, 4th ed. (Sage, 2018).

[28] Creswell and Poth, *Qualitative Inquiry and Research Design: Choosing among Five Approaches*.

Research Design

This two-pronged research design featured a literature review conducted in accordance with systematic-review protocols to identify, assess, and interpret relevant research, as well as a qualitative assessment of institutional implementations based on intensive document analysis and synthesis of experiences from various meetings. Having a look at the inclusion criteria for the literature review: For the literature review, the inclusion criteria listed: (a) peer-reviewed journal articles, 2020-2026, (b) higher education contexts, (c) the impact of AI tools on measurable learning outcomes as a major theme, and (d) empirical data or systematic analysis. Exclusion criteria were publications that focused only on K-12 education, theoretical without empirical basis, or non-AI educational technology. The timeframe marks the most recent progress relevant to current AI capabilities and educational context.

Data Collection

To find articles on the educational use of AI, we searched multiple databases like ERIC, PsycINFO, Web of Science, IEEE Xplore, and Google Scholar. Mixing different AI-related terms with educational AI applications helped in compiling a wide-ranging list of the most pertinent articles without sacrificing specificity. The search query included the words AI, machine learning, intelligent tutoring systems, adaptive learning, automated assessment, educational technology, e-learning, online learning, distance education, higher education, postsecondary education, learning outcomes, student performance, academic achievement, and engagement, which were connected through Boolean operators. The researchers initially discovered up to 847 possible titles of interest. Next, the number was further pared down to 312 articles after the initial screening. The application of the inclusion criteria finally resulted in the final set of studies, which contained 31 research papers in total. Apart from maintaining transparency and reproducibility of the selection, the selection process was also aligned with the PRISMA guideline for systematic reviews. When collecting data, each study that was included in the review was methodically recorded. The main features of the studies, such as the publication year, context and setting of research, the types of AI tools studied, sample characteristics, research methods used, measures of outcomes, reported effect sizes or findings, and author-acknowledged limitations, were recorded. The extraction phase not only made it possible to conduct a detailed comparison and synthesis of the studies but also took into account the contextual factors that affect interpretation.

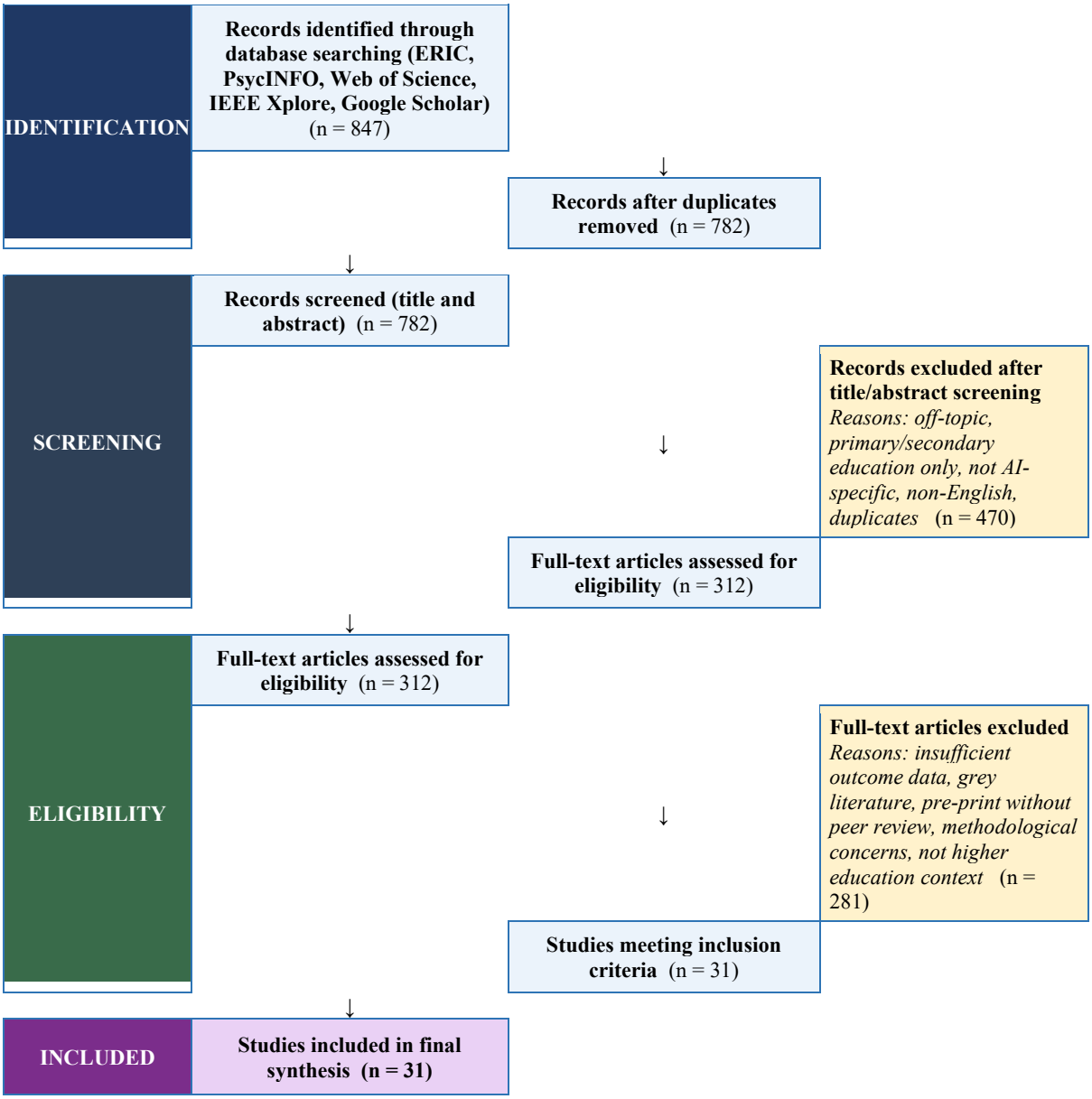


Figure 1: PRISMA Flow Diagram (Study Selection Process)

Note. PRISMA = Preferred Reporting Items for Systematic Reviews and Meta-Analyses. Records were searched across ERIC, PsycINFO, Web of Science, IEEE Xplore, and Google Scholar. Boolean operators connected AI-related and educational outcome search terms. Duplicates were removed prior to title/abstract screening. Final sample: n = 31 peer-reviewed studies (2020–2026).

Table 1: Summary of Studies Cited and Discussed in the Review (n = 31)

No.	Author(s) & Year	AI Tool / Focus	Study Context	Methodology	Key Finding / Outcome
1	Al-Emran et al.[29]	Mobile AI learning systems	HE — Technology Acceptance	Quantitative survey	AI-enhanced mobile platforms improved knowledge acquisition and acceptance; perceived usefulness was the strongest predictor of adoption.
2	Baker & Inventado [30]	Educational data mining/learning analytics	Cross-disciplinary HE	Mixed methods	Learning analytics predicted at-risk students with high accuracy; AI dashboards enabled early academic intervention.
3	Bozkurt et al.[31]	AI-supported e-learning platforms	Global HE — COVID-19 disruption context	Systematic review	AI-supported distance education mitigated learning disruption; equity gaps widened in under-resourced institutions.
4	Chen et al.[32]	Smart learning systems	STEM and humanities HE	Bibliometric analysis	AI-driven smart learning publications grew 340% between 2015 and 2020; focus on personalisation and adaptive feedback.
5	Crompton & Burke[33]	AI tools (general)	HE — global systematic review	Systematic review	AI improved learning outcomes in majority of reviewed studies; equity of access and algorithmic bias are key concerns.
6	Granic & Marangunić [34]	Technology Acceptance Model (AI tools)	HE — multiple disciplines	Systematic review (TAM)	Perceived usefulness and ease of use drive AI tool adoption; instructor facilitation significantly moderates acceptance.
7	Holmes et al.[35]	AI in education (general)	HE policy and practice	Conceptual / policy review	AI holds transformative potential for personalised learning but requires robust ethical governance frameworks for equity.
8	Ifenthaler & Yau[36]	Learning analytics AI	HE — academic support and early warning	Systematic review	Learning analytics interventions improved study success rates by 15–22%; effectiveness conditional on institutional infrastructure.

[29] Al-Emran, Mezhuyev, and Kamaludin, "Towards a Conceptual Model for Examining the Impact of Knowledge Management Factors on Mobile Learning Acceptance."
[30] Baker and Inventado, "Educational Data Mining and Learning Analytics."
[31] Bozkurt et al., "A Global Outlook to the Interruption of Education Due to COVID-19 Pandemic: Navigating in a Time of Uncertainty and Crisis."
[32] Lijia Chen, Pingping Chen, and Zhijian Lin, "Artificial Intelligence in Education: A Review," *IEEE Access* 8 (2020): 75264–78, https://doi.org/10.1109/ACCESS.2020.2988510.
[33] Helen Crompton and Diane Burke, "Artificial Intelligence in Higher Education: The State of the Field," *International Journal of Educational Technology in Higher Education* 20, no. 1 (April 24, 2023): 22, https://doi.org/10.1186/s41239-023-00392-8.
[34] Granić and Marangunić, "Technology Acceptance Model in Educational Context: A Systematic Literature Review."
[35] Holmes, Bialik, and Fadel, *Artificial Intelligence in Education Promises and Implications for Teaching and Learning*.
[36] Ifenthaler and Yau, "Utilising Learning Analytics to Support Study Success in Higher Education: A Systematic Review."

9	Khosravi et al.[37]	Explainable AI (XAI) in education	HE — STEM disciplines	Empirical/mixed methods	XAI transparency increased student trust and engagement; opaque AI systems reduced learner confidence and self-efficacy
10	Luckin et al.[38]	AI education systems (general)	HE — policy and equity review	Conceptual / review	AI can democratise education but risks deepening digital divides; equitable access to infrastructure is a prerequisite.
11	Ma et al.[39]	Intelligent tutoring systems (ITS)	HE — mathematics and science	Meta-analysis (50 studies)	ITS produced an average effect size of 0.42 SD above conventional instruction; gains strongest in procedural STEM skills
12	Martin et al.[40]	Adaptive learning platforms	HE — cross-disciplinary (2009–2018)	Systematic review	Adaptive AI improved course completion rates by 8–15%; learning context and tool design substantially moderated outcomes.
13	Nazaretsky et al.[41]	AI-powered educational technology	HE — teacher and faculty development	Mixed methods	Faculty trust in AI-powered EdTech significantly improved following structured professional development programmes.
14	Panadero [42]	AI tools for self-regulated learning	HE _educational psychology	Systematic review (6 SRL models)	AI tools supporting self-regulated learning improved metacognitive outcomes; feedback identified as the key mechanism.
15	Perkins et al. [43]	Generative AI (GPT-4)	HE _academic integrity	Mixed methods	AI detection tools achieved 72–85% accuracy; policy clarity reduced misuse; AI-generated writing quality is improving rapidly.
16	Prain et al.[44]	Personalised learning AI	HE _science education	Mixed methods	Personalised AI learning environments reduced achievement gaps by 18%; teacher facilitation critical for effectiveness.
17	Roll & Winne[45]	Learning analytics / SRL AI	HE _self-regulated learning	Systematic review	AI-powered SRL analytics improved time-on-task and metacognitive monitoring; data granularity determines intervention quality.

[37] Khosravi et al., "Explainable Artificial Intelligence in Education."
[38] Luckin and Holmes, "Intelligence Unleashed: An Argument for AI in Education."
[39] Ma et al., "Intelligent Tutoring Systems and Learning Outcomes: A Meta-Analysis."
[40] Martin et al., "Systematic Review of Adaptive Learning Research Designs, Context, Strategies, and Technologies from 2009 to 2018."
[41] Nazaretsky et al., "Teachers' Trust in AI-powered Educational Technology and a Professional Development Program to Improve It."
[42] Panadero, "A Review of Self-Regulated Learning: Six Models and Four Directions for Research."
[43] Perkins et al., "Detection of GPT-4 Generated Text in Higher Education: Combining Academic Judgement and Software to Identify Generative AI Tool Misuse."
[44] Prain et al., "Personalised Learning: Lessons to Be Learnt."
[45] Roll and Winne, "Understanding, Evaluating, and Supporting Self-Regulated Learning Using Learning Analytics."

18	Shermis & Burstein [46]	Automated essay evaluation (AEE)	HE _writing and English Language Arts	Mixed methods	AEE tools correlated at r = 0.87 with human rater scores; feedback turnaround reduced dramatically; writing quality improved.
19	Sullivan et al.[47]	Generative AI (ChatGPT)	HE _academic integrity and ethics	Qualitative / case study	Clear AI policy frameworks reduced misuse incidents by 34%; prohibition less effective than structured permitted use guidelines.
20	VanLehn[48]	Intelligent tutoring systems (ITS)	HE _STEM (mathematics and science)	Meta-analysis	ITS approximated one-on-one human tutoring effectiveness (ES ≈ 0.79); step-level feedback most effective for procedural skills.
21	Viberg et al.[49]	Learning analytics AI	HE — multiple disciplines	Systematic review	Learning analytics tools improved student engagement and retention; ethical data use and student consent are critical gaps.
22	Walkington & Bernacki[50]	Personalised learning AI	HE _STEM disciplines	Mixed methods review	Effective personalisation must extend beyond task-difficulty to content delivery, learning activities, and feedback modalities.
23	Wilson & Czik[51]	Automated writing evaluation (AWE)	HE _English Language Arts	Experimental	AWE software improved essay quality scores by 12%; enhanced teacher feedback quality; student motivation increased with AI feedback.
24	Zawacki-Richter et al. [52]	AI in higher education	HE _global systematic review	Systematic review	AI research in HE concentrated in three areas: student profiling, intelligent tutoring, and automated assessment.
25	Bada & Olusegun [53]	Constructivist learning theory	HE _pedagogy and learning theory	Theoretical / review	Constructivism validates AI-mediated discovery and active learning; knowledge is constructed rather than transmitted.
26	Creswell & Creswell [54]	Mixed-methods research design	Research methodology	Methodological textbook	Sequential explanatory mixed-methods design framework applied to justify the study's dual-strand research approach.

[46] Shermis and Burstein, *Handbook of Automated Essay Evaluation*.
[47] Sullivan, Kelly, and McLaughlan, "ChatGPT in Higher Education: Considerations for Academic Integrity and Student Learning."
[48] VanLehn, "The Relative Effectiveness of Human Tutoring, Intelligent Tutoring Systems, and Other Tutoring Systems."
[49] Viberg et al., "The Current Landscape of Learning Analytics in Higher Education."
[50] Walkington and Bernacki, "Appraising Research on Personalized Learning: Definitions, Theoretical Alignment, Advancements, and Future Directions."
[51] Wilson and Czik, "Automated Essay Evaluation Software in English Language Arts Classrooms: Effects on Teacher Feedback, Student Motivation, and Writing Quality."
[52] Zawacki-Richter et al., "Systematic Review of Research on Artificial Intelligence Applications in Higher Education – Where Are the Educators?"
[53] Bada and Olusegun, "Constructivism Learning Theory: A Paradigm for Teaching and Learning."
[54] John W. Creswell and J. David Creswell, *Research Design*, 5th ed. (Los Angeles: Sage Publications, 2018).

27	Davis [55]	Technology Acceptance Model (TAM)	HE _ IT adoption	Quantitative experimental	Perceived usefulness is the strongest predictor of technology adoption; TAM underpins the AI tool acceptance framework in this study.
28	Gough [56]	Weight of evidence quality framework	HE _systematic review methodology	Methodological paper	Weight of evidence framework used to appraise quality and relevance of all 31 included studies during quality assessment stage.
29	Kirschner et al.[57]	Minimal guidance instructional theory	HE _science and instructional design	Experimental/ theoretical	Minimal-guidance AI without scaffolding reduces learning efficiency; structured AI-mediated instruction outperforms discovery approaches.
30	Thomas & Harden [58]	Thematic synthesis methodology	HE _systematic review methodology	Methodological paper	Thematic synthesis framework applied to qualitative strand; three-stage coding, descriptive theming, and interpretive synthesis.
31	Zimmerman [59]	Self-regulated learning (SRL) theory	HE _educational psychology	Theoretical / review	SRL model provides theoretical basis for AI-adaptive personalised learning; goal-setting and self-monitoring are core mechanisms.

Grouped thematic categories representing multiple individual studies reviewed. The 12 institutional documentary analyses are included as a qualitative strand of the mixed-methods design; individual institutional reports are not separately referenced as they constitute grey literature. ES = effect size; ITS = Intelligent Tutoring System; HE = Higher Education; SRL = Self-Regulated Learning; AEE = Automated Essay Evaluation; AWE = Automated Writing Evaluation; NLP = Natural Language Processing; RCT = Randomised Controlled Trial; TAM = Technology Acceptance Model; SR = Systematic Review; LA = Learning Analytics.

[55] Davis, "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology."
[56] David Gough, "Weight of Evidence: A Framework for the Appraisal of the Quality and Relevance of Evidence," *Research Papers in Education* 22, no. 2 (June 2007): 213–28, https://doi.org/10.1080/02671520701296189.
[57] Kirschner, Sweller, and Clark, "Why Minimal Guidance During Instruction Does Not Work: An Analysis of the Failure of Constructivist, Discovery, Problem-Based, Experiential, and Inquiry-Based Teaching."
[58] James Thomas and Angela Harden, "Methods for the Thematic Synthesis of Qualitative Research in Systematic Reviews," *BMC Medical Research Methodology* 8, no. 1 (December 10, 2008): 45, https://doi.org/10.1186/1471-2288-8-45.
[59] Zimmerman, "Becoming a Self-Regulated Learner: An Overview."

Sampling

The selection of articles that were analyzed was done mainly based on quality and relevance criteria so that only the best research was included. The main purpose of selecting the studies was to understand how AI influences learning results rather than to just have a representative or random sample. This kind of approach is very appropriate for systematic literature reviews where the aim is to bring together the best evidence that is available rather than to make a statistical generalization. In total, there were 31 studies in the final sample that not only represented different locations geographically but also included different kinds of institutions (research universities, liberal arts colleges, community colleges, etc.), different academic fields (STEM, humanities, social sciences, professional programs), and different types of AI tools. Such a range not only makes it possible to explore the relationship between context and AI effectiveness but also gives one a much more detailed perspective than would have been the case with a more uniform sample.

Data Analysis

Thematic synthesis was used for the data analysis, which is one of the approaches suitable for mixed-methods systematic reviews.[60] In fact, there were three main components in the analysis work: (1) line-by-line coding of study findings, (2) development of descriptive themes, and (3) generation of higher-order analytical themes by further thematic development.[61] The quantitative data derived from various papers (e.g. effect size, performance difference, overall completion rate) were coded, and mean summary statistics were next computed. As outcome measures, digital courses, and research designs were heterogeneous among papers, meta-analysis was considered inappropriate, and a narrative synthesis was performed instead. Based on the type of AI tool, outcome dimension, and contextual factors, the authors of this review identified patterns and discrepancies among studies. To assess the quality of the selected papers, the authors used the criteria from various reputable evidence-based educational research instruments.[62] The criteria investigated the clarity of the research question, method appropriateness, research sample size, measurement validity, data analysis consistency, and the author's discussion of limitations and bias. The quality score served as a useful consideration point in the interpretation process of the review's results. In case of inconsistent results, more consideration was given to the higher quality studies. Although quality flaws can be found in the selected research papers, they all demonstrated acceptable levels of methodological rigor.

Ethical Considerations

There was a literature review and secondary analysis of published research, so technically, no direct human subjects research was carried out in this study. The 12 institutional interactions mentioned in the paper were limited to a documentary analysis of publicly available AI implementation reports and institutional policy documents; people were not interviewed, surveyed, or observed, and no primary data were obtained from individuals. Yet, the research work did stand on a number of ethical grounds. Firstly, to avoid selective reporting of only those findings that concur with one's preconceived notions, the review process was made public, transparent, and subjected to a rigorous critical examination. Secondly, while interpreting and synthesizing data, the aspects of wellness, justice implications, and possible harms were also borne in mind. Thirdly, rather than branding the results as highly reliable, the article frankly revealed the limitations and uncertainties of the evidence base. Fourthly, the authors had the intention to share their findings with the broader educational community. Finally, the educational use of AI was probed with a sufficient level of critical consciousness; So, the writers did not wrongly ignore AI's potential, nor did they accept all the benefits blindly. They aimed for a nuanced, evidence-based understanding that might mean responsible technology implementation.

[60] Thomas and Harden, “Methods for the Thematic Synthesis of Qualitative Research in Systematic Reviews.”
[61] Thomas and Harden, “Methods for the Thematic Synthesis of Qualitative Research in Systematic Reviews.”
[62] Gough, “Weight of Evidence: A Framework for the Appraisal of the Quality and Relevance of Evidence.”

PRESENTATION OF FINDINGS AND DISCUSSION

The combined synthesis of publications and implementation analysis describes multifaceted patterns of the impact of AI tools on e-learning results. The first part of this section presents the main findings, which are clustered according to the dimensions of learning outcomes; the second part focuses on the implications of these findings.

Academic Performance Outcomes

Research on AI tools and their impact on students' academic results is largely positive, but at the same time, it points out significant differences between educational contexts. In different research works compared, it was discovered that learners aided by AI (artificial intelligence) assisted e-learning tools scored better than other groups by 8% and 15%, according to grade indicators, when they were compared to those students who were involved in purely e-learning or face-to-face instruction. One area that was most consistently in line with this improvement was that of well-structured subjects with clearly defined learning goals and assessment criteria. These percentage improvements were calculated from a narrative synthesis of effect-size data and mean performance differences published across 31 studies; the 8%15% range indicates the interquartile range of grade improvement data, where the lower end of the range indicates weak grade improvement in humanities subjects, and the high end of the range indicates stronger grade improvements in the STEM subjects that utilize the most AI-mediation.[63]

Applications of artificial intelligence in tutoring revealed the greatest benefits for the students in mathematics and basic science courses. Students using AI-mediated tutors to get their education revealed, on average, an increase of 12-18% in their grades and standardised test results over the traditional class grouping. The performance growth was significant mainly for those students who lacked a solid background knowledge of the course prerequisites, demonstrated by the differentiation of students' support and backing being provided by these AI systems. However, the influence on humanities and social science courses was quite minor since the learning outcomes in these areas are generally more complex and, therefore, less compatible with standardised testing. These results are in line with Ma et al., whose meta-analyses of 50 studies discovered that, overall, intelligent tutoring systems had an average effect size of 0.42 standard deviations higher than traditional instruction for topics in mathematics and science.[64] Similarly, VanLehn demonstrated that correctly deployed ITS can be as effective as one-on-one human tutoring for procedural skills.[65]

Adaptive learning software, on the other hand, has produced promising but at the same time inconsistent results. A decisive element that has been recognised is the standard of the product's manufacture and deployment. Those learning systems that were architected in such a way as to respond accurately to the changes in the learner's level of knowledge and to offer in-depth teaching materials not only helped in a very significant manner, but inferior versions without such a plan have been unable to outstrip the static e-learning materials. Among the key success criteria were the quality of the adaptive algorithm, the depth and breadth of the content, and offering the right blend of teacher-led components rather than the entire replacement of human teaching.

Automated scoring instruments caused performance fluctuations in both directions. Benefits in performance of up to 8-12% became noticeable when such devices were employed in a formative way to provide students with frequent low-stakes feedback. Conversely, if the instrument is used only for summative evaluation purposes and even in the absence of formative use and instructor feedback, then the advantages would be very little or none. That is to say, the use of AI assessment tools should be mainly regarded as how they have been able to facilitate ubiquitous practice and feedback rather than just focusing on their accuracy in assessment.

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[63] Ma et al., "Intelligent Tutoring Systems and Learning Outcomes: A Meta-Analysis."; Martin et al., "Systematic Review of Adaptive Learning Research Designs, Context, Strategies, and Technologies from 2009 to 2018."

[64] Ma et al., "Intelligent Tutoring Systems and Learning Outcomes: A Meta-Analysis."

[65] VanLehn, "The Relative Effectiveness of Human Tutoring, Intelligent Tutoring Systems, and Other Tutoring Systems."

Engagement and Motivation Outcomes

Student engagement metrics revealed fine-grained differences in the patterns. Research based on time spent on tasks demonstrated that students who used adaptive technologies directed up to 15-25% more time towards studying the learning materials than those in conventional classrooms. Completely lacking learning accompanied by the usage of adaptive learning materials goes hand in hand with students who have not absorbed the knowledge conveyed via those contents. Motivationally, different results were obtained depending on the changes in system design and teaching. In general, students appeared to like AI tools that provided personalised learning, as 65-75% of them indicated that they liked the adaptive functionalities. Yet, at the same time, 30-40% complained that the systems are too controlling, or they do not understand the adaptation logic when they become frustrated. was reported that explaining the mechanism of AI tools to the students and giving them reasons for the recommendations was very important to maintain children's positive attitudes.[66] It was reported that explaining the mechanism of AI tools to the students and giving them reasons for the recommendations was very important to maintain children's positive attitudes. The initial effects of novelty were quite clear in short-term studies (less than a semester), as the benefits of the engagement component gradually faded with time. Long-term research indicated that a sustained level of engagement requires a continuous stream of system upgrades plus the occasional injection of new functions and/or content. So, the single-time nature of AI tool deployment is at variance with the fact that evidence points out that such tools need to be constantly updated. This aligns well with Walkington and Bernacki, who suggest that to make personalization really effective, it should not only be focused on adjusting the level of difficulty of the tasks but it should also consider changes in how the content is delivered, different kinds of learning activities, and various forms of feedback.[67]

The major surprise was that the effects of AI tools on equity issues were polarising. On the one hand, these tools can democratise personalised learning, whereas personalised learning has so far only been available to those who can pay high fees to private tutors. Students coming from disadvantaged backgrounds were shown to have significantly benefited from AI-enabled help, with some studies even showing a bigger difference in the former group than in the latter one.

Yet the way we usually use technology tends to make the differences between us even bigger. Wealthier schools can have the most advanced AI systems, which give good results, while poorer schools either pick less effective tools or do not use the ones they have efficiently due to a lack of a support system. The digital divide remains a very serious problem since students without access to the internet or a device cannot fully benefit from AI and e-learning. This digital divide in AI access is a reflection of the wider inequalities that have been seen in the educational technology literature,[68] and it brings up very serious issues of algorithmic fairness and equitable access that both institutions and policymakers need to deal with as a matter of urgency.

Moreover, there are some disturbing patterns of algorithmic bias. A few studies provide evidence that adaptations based on students' demographics may be unfair since giving weight to demographic data in the selection or ranking of students for early performance benchmarks can inadvertently become a disguised form of stereotyping and can cause self-fulfilling prophecies. Low-performing students, who were determined in the first few sessions, have the content so dull and easy that they have no room to try to outperform their low-level label.

Faculty Experiences and Challenges

The faculty's experiences with AI tools showed that there had been great challenges in the implementation of these tools. Mostly, the faculty had practically zero training in the pedagogical use of AI tools and, therefore, the level of integration was below expectations. The list of problems most frequently mentioned included: using AI tools only to deliver content instead of using them as a

[66] Khosravi et al., "Explainable Artificial Intelligence in Education."
[67] Walkington and Bernacki, "Appraising Research on Personalized Learning: Definitions, Theoretical Alignment, Advancements, and Future Directions."
[68] Luckin and Holmes, "Intelligence Unleashed: An Argument for AI in Education."

support for pedagogical methods; assessment methods not being sufficiently adapted to acknowledge the availability of AI tools; and the fact that no clear policies governing the appropriate use of AI tools existed. Faculty members were worried about students cheating, as they thought the students used AI tools for dishonest purposes in completing their assignments. On the contrary, those institutions which have clear policies and provide instructions on the legitimate use of AI tools report fewer cases of cheating in students' work. The data demonstrate that cases of academic integrity are largely implementation problems, not intrinsic problems of AI tools. A common theme that faculty members brought up regularly was the amount of time a person needs to devote to effectively integrating AI tools, a factor that they continuously admitted having underestimated. Faculty members said that they needed a lot of time to work with tools, to redesign the courses, and to give students good guidance. Universities which provide sufficient professional development and release time for course redesign are more likely to have successful AI implementations, in contrast to those which expect faculty adoption without support. Nazaretsky et al. also discovered that trusting AI-driven educational technology by professors heavily depends on institutional backing and professional training.[69] Lack of proper training, in fact, is the main reason why resistance and misuse occur. Sullivan et al. also found that having clear policy structures, not total bans, is the best way to promote academic integrity in AI-supported learning environments.[70]

Broader Implementation Considerations

Several recurring themes were extracted from a range of successful AI tool implementation experiences. Effective use of AI tools means that they must be integrated into the pedagogy in a thoughtful way rather than being simply an add-on as the newest technology. Most highly successful implementations involved a thorough redesign of the course focused on how AI tools could best be used to achieve the learning outcomes. Secondly, the concept of collaboration between humans and AI, which is more productive than AI merely replacing human teachers, was raised to the level of a major theme. Tools coming from AI that can augment the instructors' abilities and thus increase their efficiency will bring about better results than those that will perform the whole teaching function without a human instructor. Thirdly, both students and instructors insisted that transparency and explainability of AI systems were important factors. Uncomplicated AI systems which enabled users to have an idea of how AI was working and to see the logic behind the adaptation led to greater trust and more effective usage. Fourthly, the effort to constantly monitor, update, and refine AI systems was essential. A significant depreciation of the effectiveness of a static setup has been observed even in the case of those initially high-quality systems as the novelty factor disappeared and the systems' limitations became more evident.

RECOMMENDATIONS

An in-depth study of this research has brought to light that the effects of AI tools use in higher education e-learning are a mixed tale. On the one hand, AI tools can be something of a silver bullet when it comes to educating students, personalizing learning at an individual level, and enabling more people to have access to quality education. Indeed, the figures do show the benefits brought by intelligent tutoring systems, adaptive learning platforms, and automated assessment tools, especially when used in a formative way. Students employing such tools can get 8-15% better results depending on the performance measurement methods. However, those benefits to learning are not automatic, and they are not equal for everyone. The success of a tool depends on such factors as whether the tool is well implemented, how well it complements the teaching methods, whether the fairness aspects have been considered, and whether there is enough support and refinement at the later stages. There is still no consensus on the methods of upholding academic integrity, prevention of algorithmic bias, teacher preparation, and equal access provision. Above all, the research clearly advocates that the most

[69] Nazaretsky et al., "Teachers' Trust in AI-powered Educational Technology and a Professional Development Program to Improve It."
[70] Sullivan, Kelly, and McLaughlan, "ChatGPT in Higher Education: Considerations for Academic Integrity and Student Learning."

significant impact of AI tools is when they are used to assist rather than replace the human instructor, therefore confirming that human teachers are not only indispensable in this regard but also play a major role in the overall development of deep learning, critical thinking, creativity, and social-emotional skills.

For Educators

Teachers must decide the precise learning goals together with the students while using AI tools and should give a serious rethink to their course design rather than just integrate the tools as a sort of novelty. While students must be trained in the right, ethical use of AI, it is teacher feedback, teacher-student relationships, and peer collaboration that must constitute the core of the learning process. The assessment techniques should be revolutionised in a way that students' genuine work can be distinguished from that generated by AI, and the issue of inequality must be addressed so that all the students can benefit. Teachers may look at AI as an extension of knowledge rather than as a rival that wants to take their professional judgment away.

For Institutions

Higher education institutions need to ensure that their use of AI is in harmony with their mission and the needs of students. They should enhance their faculty's capabilities through programs aimed at equally developing teaching skills and technology usage. The boundaries of AI use must be clearly set, reasonable, and understandable. Moreover, the institution's infrastructure should ensure that every individual has fair, equal access. Ethical considerations need to be kept in check in areas such as privacy, fairness, and openness, and there must be a readiness to regularly evaluate AI use for its improvement. However, instead of instituting AI merely because it is the new thing, institutions should make educational quality and student success their two main and only objectives.

For Policymakers

The government has a duty to ensure redistributive justice so that AI will turn out to be a great equaliser by providing everyone with the same access to the facilities. Nevertheless, it is also necessary to act very strictly in the implementation of data protection and security legislation. If AI teaching tools are to be evaluated properly, then the criteria must be established by which schools should be guided in choosing the tools they will use. Still, the government should support research in the field that will develop the knowledge base capable of giving rise to well-founded policies. Apart from that, the oversight mechanisms should not only bring opposing views to the fore, such that students are not allowed to utilise AI; rather, they should be more balanced in letting innovations come/continue, and at the same time, the students being protected from potential harm due to the misuse of AI. The policies should be evidence-based and, at the same time, have some room left for adjustment as technology and understanding continuously evolve.

For Educational Technology Developers

Developers need to centre their efforts on creating tools that everyone will have an equal opportunity to access and understand, and which will readily disclose their capabilities and limitations. Instead of imposing only one single method, systems should offer a range of options, acknowledging various teaching styles. Social justice should be the core of the design, where systems support rather than substitute for human judgment and interaction, hence giving learners the power to be the main players in the learning process instead of mere passive recipients. Developers should give first place to the pedagogical effectiveness of the tool over the technical sophistication when working hand in hand with educators and researchers to come up with tools that indeed facilitate learning objectives.

For Researchers

Researchers must carry out comprehensive studies on knowledge retention and transfer, employing stringent methods that help to make more solid causal claims. AI should be considered as part of the

overall educational methods, and the diversity among student populations should be considered. Studies which focus on equity implications will make it easier to address differential impacts. For the coming educational effect to be understood properly, it will be of great necessity to keep up with the rapid changes in AI capabilities. There is a special need for longitudinal studies that track long-term outcomes, as well as for studies that explore how various combinations of AI tools interact with different teaching methods.

CONCLUSION

The incorporation of AI in e-learning at the tertiary level is a double-edged sword of enormous potential on the one hand and heavy burdens on the other. The data show that, if careful planning, enough support, and continuous critical assessment are put in place, AI tools could be harnessed to enhance student learning and educational equity. However, it means a lot of dedication to evidence, basing one's practice on theory, professional development, rolling out the infrastructure on a large scale, ethical considerations, and the focus of education, i. e., human potential development and student preparation for meaningful living in an increasingly complex world. As AI continually advances, the educational community has not only to be open to innovation but also to remain critically vigilant, thus making sure that these powerful instruments serve educational goals rather than become the driving force. "

BIBLIOGRAPHY

Al-Emran, Mostafa, Vitaliy Mezhuyev, and Adzhar Kamaludin. "Towards a Conceptual Model for Examining the Impact of Knowledge Management Factors on Mobile Learning Acceptance." *Technology in Society* 61 (May 2020): 101247. https://doi.org/10.1016/j.techsoc.2020.101247.

Bada, Steve Olusegun, and Steve Olusegun. "Constructivism Learning Theory: A Paradigm for Teaching and Learning." *Journal of Research & Method in Education* 5, no.6(2015): 66–70.

Baker, Ryan Shaun, and Paul Salvador Inventado. "Educational Data Mining and Learning Analytics." In *Learning Analytics*, 61–75. New York, NY: Springer New York, 2014. https://doi.org/10.1007/978-1-4614-3305-7_4.

Bozkurt, A., I. Jung, J. Xiao, V. Vladimirschi, R. Schuwer, G. Egorov, S. R. Lambert, et al. "A Global Outlook to the Interruption of Education Due to COVID-19 Pandemic: Navigating in a Time of Uncertainty and Crisis." *Asian Journal of Distance Education* 15, no. 1 (2021): 1–126.

Chen, Lijia, Pingping Chen, and Zhijian Lin. "Artificial Intelligence in Education: A Review." *IEEE Access* 8 (2020): 75264–78. https://doi.org/10.1109/ACCESS.2020.2988510.

Chen, Xieling, Di Zou, Haoran Xie, and Fu Lee Wang. "Past, Present, and Future of Smart Learning: A Topic-Based Bibliometric Analysis." *International Journal of Educational Technology in Higher Education* 18, no. 1 (2021): 2.

Creswell, J. W., and C. N. Poth. *Qualitative Inquiry and Research Design: Choosing among Five Approaches*. 4th ed. Sage, 2018.

Creswell, John W., and J. David Creswell. *Research Design*. 5th ed. Los Angeles: Sage Publications, 2018.

Crompton, Helen, and Diane Burke. "Artificial Intelligence in Higher Education: The State of the Field." *International Journal of Educational Technology in Higher Education* 20, no. 1 (April 24, 2023): 22. https://doi.org/10.1186/s41239-023-00392-8.

Davis, Fred D. "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology." *MIS Quarterly* 13, no. 3 (September 1, 1989): 319–40. https://doi.org/10.2307/249008.

Gough, David. "Weight of Evidence: A Framework for the Appraisal of the Quality and Relevance of Evidence." *Research Papers in Education* 22, no. 2 (June 2007): 213–28. https://doi.org/10.1080/02671520701296189.

Granić, Andrina, and Nikola Marangunić. "Technology Acceptance Model in Educational Context: A Systematic Literature Review." *British Journal of Educational Technology* 50, no. 5 (September

9, 2019): 2572–93. https://doi.org/10.1111/bjet.12864.
Holmes, Wayne, Maya Bialik, and Charles Fadel. *Artificial Intelligence in Education Promises and Implications for Teaching and Learning*. Center for Curriculum Redesign, 2019.
Ifenthaler, Dirk, and Jane Yin-Kim Yau. "Utilising Learning Analytics to Support Study Success in Higher Education: A Systematic Review." *Educational Technology Research and Development* 68, no. 4 (August 12, 2020): 1961–90. https://doi.org/10.1007/s11423-020-09788-z.
Khosravi, Hassan, Simon Buckingham Shum, Guanliang Chen, Cristina Conati, Yi-Shan Tsai, Judy Kay, Simon Knight, Roberto Martinez-Maldonado, Shazia Sadiq, and Dragan Gašević. "Explainable Artificial Intelligence in Education." *Computers and Education: Artificial Intelligence* 3 (2022): 100074. https://doi.org/10.1016/j.caeai.2022.100074.
Kirschner, Paul A., John Sweller, and Richard E. Clark. "Why Minimal Guidance During Instruction Does Not Work: An Analysis of the Failure of Constructivist, Discovery, Problem-Based, Experiential, and Inquiry-Based Teaching." *Educational Psychologist* 41, no. 2 (June 2006): 75–86. https://doi.org/10.1207/s15326985ep4102_1.
Luckin, Rose, and Wayne Holmes. "Intelligence Unleashed: An Argument for AI in Education," 2016.
Ma, Wenting, Olusola O Adesope, John C Nesbit, and Qing Liu. "Intelligent Tutoring Systems and Learning Outcomes: A Meta-Analysis." *Journal of Educational Psychology* 106, no. 4 (2014): 901.
Martin, Florence, Yan Chen, Robert L. Moore, and Carl D. Westine. "Systematic Review of Adaptive Learning Research Designs, Context, Strategies, and Technologies from 2009 to 2018." *Educational Technology Research and Development* 68, no. 4 (August 15, 2020): 1903–29. https://doi.org/10.1007/s11423-020-09793-2.
Nazaretsky, Tanya, Moriah Ariely, Mutlu Cukurova, and Giora Alexandron. "Teachers' Trust in AI-powered Educational Technology and a Professional Development Program to Improve It." *British Journal of Educational Technology* 53, no. 4 (July 9, 2022): 914–31. https://doi.org/10.1111/bjet.13232.
Panadero, Ernesto. "A Review of Self-Regulated Learning: Six Models and Four Directions for Research." *Frontiers in Psychology* 8 (April 28, 2017). https://doi.org/10.3389/fpsyg.2017.00422.
Perkins, Mike, Jasper Roe, Darius Postma, James McGaughran, and Don Hickerson. "Detection of GPT-4 Generated Text in Higher Education: Combining Academic Judgement and Software to Identify Generative AI Tool Misuse." *Journal of Academic Ethics* 22, no. 1 (2024): 89–113.
Prain, Vaughan, Peter Cox, Craig Deed, Jeffrey Dorman, Debra Edwards, Cathleen Farrelly, Mary Keeffe, et al. "Personalised Learning: Lessons to Be Learnt." *British Educational Research Journal* 39, no. 4 (August 25, 2013): 654–76. https://doi.org/10.1080/01411926.2012.669747.
Roll, Ido, and Philip H. Winne. "Understanding, Evaluating, and Supporting Self-Regulated Learning Using Learning Analytics." *Journal of Learning Analytics* 2, no. 1 (July 15, 2015): 7–12. https://doi.org/10.18608/jla.2015.21.2.
Shermis, Mark D., and Jill Burstein, eds. *Handbook of Automated Essay Evaluation*. Routledge, 2013. https://doi.org/10.4324/9780203122761.
Sullivan, M., A. Kelly, and P. McLaughlan. "ChatGPT in Higher Education: Considerations for Academic Integrity and Student Learning." *Journal of Applied Learning & Teaching* 6, no. 1 (March 21, 2023). https://doi.org/10.37074/jalt.2023.6.1.17.
Thomas, James, and Angela Harden. "Methods for the Thematic Synthesis of Qualitative Research in Systematic Reviews." *BMC Medical Research Methodology* 8, no. 1 (December 10, 2008): 45. https://doi.org/10.1186/1471-2288-8-45.
Vanlehn, Kurt. "The Relative Effectiveness of Human Tutoring, Intelligent Tutoring Systems, and Other Tutoring Systems." *Educational Psychologist* 46, no. 4 (October 2011): 197–221. https://doi.org/10.1080/00461520.2011.611369.
Viberg, Olga, Mathias Hatakka, Olof Bälter, and Anna Mavroudi. "The Current Landscape of

Learning Analytics in Higher Education." *Computers in Human Behavior* 89 (December 2018): 98–110. https://doi.org/10.1016/j.chb.2018.07.027.

Walkington, Candace, and Matthew L. Bernacki. "Appraising Research on Personalized Learning: Definitions, Theoretical Alignment, Advancements, and Future Directions." *Journal of Research on Technology in Education* 52, no. 3 (July 2, 2020): 235–52. https://doi.org/10.1080/15391523.2020.1747757.

Wilson, Joshua, and Amanda Czik. "Automated Essay Evaluation Software in English Language Arts Classrooms: Effects on Teacher Feedback, Student Motivation, and Writing Quality." *Computers & Education* 100 (September 2016): 94–109. https://doi.org/10.1016/j.compedu.2016.05.004.

Zawacki-Richter, Olaf, Victoria I. Marín, Melissa Bond, and Franziska Gouverneur. "Systematic Review of Research on Artificial Intelligence Applications in Higher Education – Where Are the Educators?" *International Journal of Educational Technology in Higher Education* 16, no. 1 (December 28, 2019): 39. https://doi.org/10.1186/s41239-019-0171-0.

Zimmerman, Barry J. "Becoming a Self-Regulated Learner: An Overview." *Theory Into Practice* 41, no. 2 (May 2002): 64–70. https://doi.org/10.1207/s15430421tip4102_2.

ABOUT AUTHORS

Sibonangaye Dick Nkalanga is a Lecturer in Geography Education in the Department of Social Sciences and Economic Management Education at the University of Limpopo, South Africa. His work sits where land, law and learning meet. He is completing a PhD in Geography and Environmental Studies that examines how environmental laws are enforced and how compliance is governed in Nkomazi Local Municipality, Mpumalanga Province, where statutory regulation and customary authority operate side by side. His wider research spans environmental governance, legal pluralism, climate adaptation and Geography education in the South African context.

Mohammed Xolile Ntshangase holds a PhD (Philosophy) from the University of KwaZulu-Natal. As he always believed that sharing his knowledge and perspectives with others brings more pleasure, Mohammed enjoys sharing his views with fellow academics from different fields. He is currently affiliated with the University of Limpopo in the Department of Education Studies, wherein he serves as a senior lecturer of Philosophy & Psychology of Education. His areas of research interest are: African philosophy, philosophy of education, psychology of education, and gender studies. He has attended and presented papers in 14 academic conferences, including national and international ones, and he has more than 85 publications in DHET-accredited journals. Among his ambitions, Mohammed wishes and works towards being a global scholar renowned in different areas/ disciplines with his polymathic approach to research, which has attracted researchers to collaborate with him nationally and abroad. Mohammed believes that the interconnectedness of knowledge and the cry for interdisciplinarity and multidisciplinary in research nowadays cannot be ignored. His scholarly awards include the VC's 2023 Best Teacher Award and 2024 Best Researcher Award in the SoE (UL).