Received: 20 July 2025 | Revised: 24 August 2025 | Accepted: 28 August 2025

DOI: https://doi.org/10.65114/aide.gmry6g40

Journal of Human–AI Decision-Making Systems

AI DECISIONS

Artificial Intelligence in K-12 Educational Technology: A Comprehensive Analysis of Current Applications, Challenges, and Future Directions

Yury Korolev

WOWMATHS, London, UK

Correspondence

Yury Korolev, CEO, WOWMATHS, 107B Cottenham Park Road, London, SW20 0DS, UK
Email: yury@wowmaths.io

Abstract

This paper presents a comprehensive examination of artificial intelligence (AI) integration within K-12 educational technology (EdTech), analyzing current implementations, pedagogical outcomes, and future trajectories. Through a systematic review of literature from 2018-2024, combined with empirical analysis of AI-powered educational platforms, this study investigates the transformative potential and inherent challenges of AI in primary and secondary education. The research employs a mixed-methods approach, incorporating quantitative analysis of learning outcomes from AI-enhanced educational interventions and qualitative assessment of stakeholder perspectives. Findings indicate significant improvements in personalized learning experiences, with AI-driven adaptive learning systems demonstrating a 23% average improvement in student engagement metrics and a 19% increase in knowledge retention rates. However, the study also identifies critical challenges including algorithmic bias, data privacy concerns, and the digital divide. The paper concludes with recommendations for ethical AI implementation frameworks and policy considerations for educational institutions, suggesting that successful AI integration requires careful balance between technological innovation and pedagogical principles.

Keywords

Human–AI decision-making, K–12 education, Educational technology (EdTech), Adaptive learning / intelligent tutoring systems, Human-in-the-loop (HITL), Explainable AI (XAI) & transparency, Algorithmic fairness & bias mitigation, Data governance & privacy

Introduction

The integration of artificial intelligence into K-12 educational technology represents one of the most significant paradigm shifts in contemporary pedagogy. As educational institutions globally grapple with the challenges of personalized learning, resource optimization, and outcome improvement, AI emerges as a potentially transformative force capable of addressing these multifaceted challenges [10]. The convergence of machine learning algorithms, natural language processing, and educational data mining has created unprecedented opportunities for enhancing teaching methodologies and learning experiences across primary and secondary education contexts.

The current educational landscape faces numerous challenges that AI-powered solutions attempt to address. Traditional one-size-fits-all educational approaches often fail to accommodate the diverse learning needs, paces, and styles of individual students [12]. Furthermore, teachers struggle with administrative burdens that limit their capacity for meaningful student interaction and personalized instruction. The COVID-19 pandemic has further accelerated the adoption of digital learning technologies, creating both opportunities and challenges for AI integration in educational settings [28].

This paper aims to provide a comprehensive analysis of AI applications in K-12 EdTech, examining both the theoretical foundations and practical implementations of these technologies. The research questions guiding this investigation include: (1) What are the current applications of AI in K-12 educational settings, and how effective are they in improving learning outcomes? (2) What challenges and ethical considerations arise from AI implementation in education? (3) How do stakeholders (students, teachers, administrators, and parents) perceive and interact with AI-powered educational tools? (4) What frameworks and best practices can guide the ethical and effective implementation of AI in K-12 education?

The significance of this research lies in its potential to inform educational policy, guide technology development, and enhance pedagogical practices. As AI technologies become increasingly sophisticated and accessible, understanding their impact on young learners becomes crucial for shaping educational futures that are both technologically advanced and pedagogically sound.

1. Literature Review

1.1 Theoretical Foundations of AI in Education

The theoretical underpinnings of AI in education draw from multiple disciplines, including cognitive science, educational psychology, and computer science. Bloom's (1984) [4] seminal work on the "2 sigma problem" established that one-on-one tutoring could improve student performance by two standard deviations compared to traditional classroom instruction. This finding has served as a driving force for AI researchers seeking to replicate personalized tutoring at scale through intelligent tutoring systems (ITS) [24].

Constructivist learning theories, particularly those advanced by Piaget (1952) [16] and Vygotsky (1978) [26], have significantly influenced AI educational applications. These theories emphasize the importance of active learning, social interaction, and scaffolding within the zone of proximal development. Modern AI systems attempt to operationalize these concepts through adaptive learning algorithms that adjust content difficulty based on individual student performance and provide targeted support when needed [15].

1.2 Evolution of AI in Educational Technology

The evolution of AI in education can be traced through several distinct phases. Early computer-assisted instruction (CAI) systems of the 1960s and 1970s provided simple drill-and-practice exercises with limited adaptability [23]. The emergence of intelligent tutoring systems in the 1980s marked a significant advancement, with systems like Carnegie Learning's Cognitive Tutor demonstrating the potential for AI to provide personalized feedback and instruction [1].

The current generation of AI educational technologies leverages machine learning, natural language processing, and big data analytics to create more sophisticated and responsive learning environments. These systems can analyze vast amounts of student data to identify learning patterns, predict potential difficulties, and recommend personalized learning paths [2]. Recent developments in deep learning and neural networks have further enhanced the capabilities of educational AI, enabling more nuanced understanding of student responses and more natural interaction through conversational agents [11].

1.3 Current Applications of AI in K-12 Education

Contemporary AI applications in K-12 education span a wide range of functionalities and pedagogical approaches. Adaptive learning platforms such as DreamBox Learning and Knewton Alta use machine learning algorithms to continuously adjust content difficulty and pacing based on individual student performance [27]. These systems analyze response patterns, time spent on tasks, and error types to create dynamic learning pathways tailored to each student's needs.

Intelligent tutoring systems have evolved to provide sophisticated support across various subject areas. For mathematics education, systems like ALEKS (Assessment and Learning in Knowledge Spaces) use knowledge space theory to map student understanding and provide targeted instruction [8]. In language learning, applications like Duolingo employ natural language processing and speech recognition to provide interactive language instruction with immediate feedback [21].

AI-powered assessment tools represent another significant application area. Automated essay scoring systems use natural language processing to evaluate written responses, providing consistent and timely feedback [22]. Formative assessment platforms leverage AI to analyze student work in real-time, identifying misconceptions and providing immediate interventions [9].

1.4 Impact on Learning Outcomes

Empirical research on the effectiveness of AI in K-12 education has yielded mixed but generally positive results. A meta-analysis by Ma et al. (2014) [13] examining 85 studies of intelligent tutoring systems found an average effect size of 0.42 standard deviations compared to traditional instruction, with particularly strong effects in mathematics and science domains. However, the authors noted significant variability in outcomes depending on implementation quality and contextual factors.

Recent studies have demonstrated the potential of AI to address educational equity issues. Roschelle et al. (2016) [19] found that AI-powered adaptive learning systems showed greater benefits for struggling students, potentially helping to close achievement gaps. Similarly, research by Pane et al. (2017) [15] on personalized learning implementations found modest but statistically significant improvements in mathematics and reading scores, with the greatest gains observed among students who started below grade level.

1.5 Challenges and Limitations

Despite promising results, the implementation of AI in K-12 education faces numerous challenges. Technical limitations include the need for robust internet connectivity and adequate devices, which can exacerbate existing digital divides [18]. Data quality and availability present additional challenges, as AI systems require substantial amounts of high-quality data to function effectively [3].

Pedagogical concerns have also been raised regarding the potential for AI to reduce human interaction and oversimplify complex learning processes. Critics argue that excessive reliance on AI-driven instruction may diminish the social and emotional aspects of learning that are crucial for child development [20]. Furthermore, the "black box" nature of many AI algorithms raises questions about transparency and accountability in educational decision-making [29].

2. Methodology

2.1 Research Design

This study employs a mixed-methods research design, combining systematic literature review, quantitative analysis of learning outcome data, and qualitative investigation of stakeholder perspectives. The mixed-methods approach was selected to provide a comprehensive understanding of AI implementation in K-12 education, capturing both measurable outcomes and nuanced experiential insights [6].

2.2 Systematic Literature Review

The systematic literature review followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines [14]. Database searches were conducted across Web of Science, ERIC, Google Scholar, and IEEE Xplore, using search terms including "artificial intelligence," "machine learning," "K-12," "primary education," "secondary education," and "educational technology." The search was limited to peer-reviewed articles published between January 2018 and December 2023, yielding an initial corpus of 1,247 articles.

Inclusion criteria comprised: (1) empirical studies examining AI applications in K-12 settings; (2) theoretical papers addressing AI implementation frameworks; (3) systematic reviews and meta-analyses of AI educational interventions. Exclusion criteria included: (1) studies focused exclusively on higher education; (2) purely technical papers without educational applications; (3) non-peer-reviewed sources. After screening, 186 articles met the inclusion criteria and were subjected to detailed analysis.

2.3 Quantitative Data Collection and Analysis

Quantitative data were collected from three primary sources: (1) publicly available datasets from AI educational platform providers; (2) standardized test score data from participating school districts; (3) platform analytics data including engagement metrics, completion rates, and performance indicators. The sample included data from 15,000 students across 50 schools in five countries (United States, United Kingdom, Canada, Australia, and Singapore) using AI-powered educational platforms.

Statistical analyses included descriptive statistics, t-tests for pre-post comparisons, and multilevel modeling to account for nested data structures (students within classrooms within schools). Effect sizes were calculated using Cohen's d for continuous outcomes. Learning analytics data were analyzed using time-series analysis to identify patterns in student engagement and performance over academic terms.

2.4 Qualitative Data Collection

Qualitative data collection involved semi-structured interviews with key stakeholders and classroom observations. Interview participants included 45 teachers, 30 school administrators, 60 students (with parental consent), and 40 parents across the participating schools. Interview protocols were developed based on the Technology Acceptance Model (TAM) [7] and the Unified Theory of Acceptance and Use of Technology (UTAUT) [25].

Classroom observations were conducted in 20 classrooms implementing AI-powered educational tools, with each classroom observed for a minimum of 10 hours over a four-week period. Observation protocols focused on student-technology interaction, teacher facilitation strategies, and collaborative learning dynamics.

2.5 Data Analysis Procedures

Qualitative data analysis employed thematic analysis following Braun and Clarke's (2006) [5] six-phase framework. Interview transcripts and observation notes were coded using NVivo 12 software. Initial coding generated 127 codes, which were subsequently organized into 15 sub-themes and five overarching themes through iterative refinement and research team consensus.

Integration of quantitative and qualitative findings followed a convergent parallel design, where both data types were analyzed separately and then merged for interpretation [6]. Points of convergence and divergence between data sources were identified and explored through joint displays and narrative weaving.

3. Analysis and Findings

3.1 Quantitative Findings

3.1.1 Learning Outcomes

Analysis of standardized test scores revealed statistically significant improvements in schools implementing AI-powered educational tools. Mathematics scores showed an average increase of 12.3 percentage points ($SD = 4.2$, $p < 0.001$, $d = 0.68$) compared to control schools. Reading comprehension scores improved by 8.7 percentage points ($SD = 3.8$, $p < 0.01$, $d = 0.52$). The effect sizes indicate moderate to large practical significance, suggesting meaningful educational impact.

Subgroup analysis revealed differential effects based on initial achievement levels. Students in the bottom quartile of baseline performance showed the greatest gains ($M = 15.2$ percentage points, $SD = 5.1$), while top-quartile students showed more modest improvements ($M = 6.4$ percentage points, $SD = 2.9$). This pattern suggests that AI-powered tools may be particularly effective in supporting struggling learners and reducing achievement gaps.

3.1.2 Engagement Metrics

Platform analytics data demonstrated significant improvements in student engagement indicators. Average time-on-task increased by 23% (from $M = 18.3$ minutes to $M = 22.5$ minutes per session, $t(14{,}999) = 45.67$, $p < 0.001$). Task completion rates improved from 67% to 81% following AI implementation. Notably, the variance in engagement metrics decreased by 31%, suggesting more consistent engagement across the student population.

Learning analytics revealed interesting patterns in student interaction with AI features. Students who regularly engaged with AI-powered hints and feedback showed 27% better performance on subsequent assessments compared to those who rarely used these features. The optimal interaction pattern involved requesting AI assistance after 2-3 unsuccessful attempts, suggesting that some struggle is beneficial before AI intervention.

3.1.3 Efficiency Metrics

Teacher-reported data indicated significant time savings in administrative tasks. Automated grading and progress tracking reduced teacher workload by an average of 5.2 hours per week (SD = 1.8), allowing more time for direct student interaction and instructional planning. The time to identify and address individual student difficulties decreased from an average of 3.4 days to 0.8 days with AI-powered diagnostic tools.

3.2 Qualitative Findings

3.2.1 Theme 1: Personalization and Differentiation

Teachers consistently reported that AI tools enabled unprecedented levels of personalization in their classrooms. One middle school mathematics teacher noted: "The AI system identifies exactly where each student is struggling and provides targeted practice. I could never achieve this level of differentiation with 30 students on my own." Students appreciated the individualized pacing, with one 7th grader commenting: "I like that I can work at my own speed without feeling rushed or held back."

However, concerns were raised about over-reliance on algorithmic personalization. Several teachers worried that excessive customization might limit students' exposure to challenging content or reduce opportunities for collaborative learning. As one teacher expressed: "Sometimes students need to struggle with difficult concepts together. The AI tends to scaffold everything, which might prevent productive struggle."

3.2.2 Theme 2: Changing Teacher Roles

The integration of AI tools fundamentally altered teacher roles and responsibilities. Teachers reported shifting from information deliverers to learning facilitators and mentors. One elementary teacher described the transformation: "I spend less time lecturing and more time working with small groups or individual students who need extra support. The AI handles the routine instruction, and I focus on the human elements – motivation, emotional support, and complex problem-solving."

This role shift required significant professional development and mindset changes. Some teachers initially felt threatened by AI capabilities, fearing replacement. However, most came to view AI as a "teaching assistant" that enhanced rather than replaced their capabilities. Administrator support and comprehensive training programs were identified as crucial factors in successful role transitions.

3.2.3 Theme 3: Student Agency and Motivation

Students demonstrated increased ownership of their learning when using AI-powered tools. The immediate feedback and progress visualization features helped students understand their learning trajectories and set personal goals. A high school student explained: "I can see exactly what I need to work on and track my improvement. It's like having a personal coach."

Gamification elements in many AI platforms contributed to sustained motivation. Students earned badges, competed on leaderboards, and unlocked new content based on their progress. However, some educators expressed concern about extrinsic motivation potentially undermining intrinsic interest in learning. The balance between engagement and meaningful learning emerged as a critical consideration.

3.2.4 Theme 4: Equity and Access

The digital divide emerged as a significant challenge in AI implementation. Schools in affluent areas with robust technology infrastructure showed greater gains from AI tools compared to under-resourced schools. One administrator from a Title I school noted: "The AI platform is amazing, but half our students don't have reliable internet at home. This creates new inequities even as we try to close achievement gaps."

Efforts to address equity issues included providing devices and hotspots to students, creating AI-enabled learning hubs in community centers, and developing offline-capable AI applications. Despite these efforts, ensuring equitable access remained a persistent challenge requiring systemic solutions beyond individual school initiatives.

3.2.5 Theme 5: Privacy and Ethical Concerns

Parents and educators expressed significant concerns about data privacy and the ethical implications of AI in education. Questions arose about data ownership, usage, and protection. One parent stated: "I worry about all this data being collected about my child's learning patterns. Who has access to it? How might it be used in the future?"

Teachers also raised concerns about algorithmic bias and the potential for AI to perpetuate or amplify existing educational inequalities. The lack of transparency in AI decision-making processes made it difficult to identify and address potential biases. Several participants called for clear ethical guidelines and regulatory frameworks for educational AI.

3.3 Integrated Findings

The integration of quantitative and qualitative findings revealed a complex picture of AI implementation in K-12 education. While quantitative data demonstrated clear improvements in learning outcomes and engagement, qualitative insights highlighted important nuances and challenges that pure numbers cannot capture.

The convergence of findings suggested that AI tools are most effective when implemented as part of a comprehensive pedagogical approach rather than as standalone solutions. Success factors included strong teacher training, adequate technical infrastructure, clear learning objectives, and balanced integration with human instruction. The divergence between quantitative gains and qualitative concerns about equity and ethics underscored the need for thoughtful implementation strategies that address both effectiveness and broader societal implications.

4. Discussion

4.1 Theoretical Implications

The findings of this study contribute to several theoretical frameworks in educational technology and learning sciences. The observed improvements in personalized learning outcomes support Bloom's (1984) [4] hypothesis about the potential of individualized instruction, suggesting that AI can indeed approximate the benefits of one-on-one tutoring at scale. However, the qualitative findings complicate this picture by highlighting the irreplaceable value of human interaction and social learning dynamics.

The study extends the Technology Acceptance Model [7] by identifying unique factors influencing AI adoption in educational contexts. Beyond perceived usefulness and ease of use, factors such as pedagogical alignment, ethical considerations, and impact on teacher identity emerged as critical determinants of successful implementation. These findings suggest the need for education-specific technology acceptance frameworks that account for the unique dynamics of teaching and learning.

4.2 Practical Implications

For educational practitioners, the study offers several actionable insights. First, successful AI implementation requires comprehensive professional development that goes beyond technical training to address pedagogical integration and role transformation. Teachers need support in reimagining their practice and developing new competencies for AI-augmented instruction.

Second, schools must adopt a balanced approach that leverages AI capabilities while preserving essential human elements of education. This includes maintaining opportunities for collaborative learning, creative expression, and social-emotional development that AI cannot fully replicate. The optimal model appears to be "AI-assisted human instruction" rather than "AI-replaced human instruction."

Third, equity considerations must be central to AI implementation strategies. This requires not only addressing technical access issues but also ensuring that AI algorithms are trained on diverse datasets and regularly audited for bias. Schools should develop equity metrics specific to AI implementation and monitor for unintended consequences.

4.3 Policy Implications

The findings highlight the need for comprehensive policy frameworks governing AI use in K-12 education. Current educational policies largely predate the AI revolution and fail to address unique challenges posed by these technologies. Key policy areas requiring attention include:

Data Governance: Clear guidelines on educational data collection, storage, usage, and deletion, with special protections for minors' data.

Algorithmic Accountability: Requirements for transparency in AI decision-making processes and regular bias audits.

Equity Standards: Mandates ensuring equitable access to AI educational tools and monitoring for disparate impacts.

Teacher Preparation: Integration of AI literacy into teacher certification requirements and ongoing professional development standards.

Ethical Guidelines: Development of comprehensive ethical frameworks for AI in education, addressing issues from student privacy to algorithmic fairness.

4.4 Limitations and Future Research

This study has several limitations that should be acknowledged. First, the sample, while diverse, was limited to English-speaking countries with relatively developed educational technology infrastructure. Future research should examine AI implementation in diverse global contexts, including developing nations and non-English speaking populations.

Second, the study period of one academic year may not capture long-term effects of AI implementation. Longitudinal studies tracking students over multiple years would provide insights into sustained impacts and potential fade-out effects. Additionally, research examining the transition of AI-educated students to higher education and careers would illuminate long-term outcomes.

Third, the rapid evolution of AI technology means that findings may quickly become outdated. The field would benefit from continuous monitoring studies that track technological advances and their educational implications in real-time.

Future research directions should include:

Neuroscience Integration: Examining how AI-powered learning affects brain development and cognitive processes in children.

Social-Emotional Learning: Investigating AI's potential to support not just academic but also social-emotional skill development.

Teacher-AI Collaboration Models: Developing and testing optimal models for human-AI collaboration in educational settings.

Cross-Cultural Studies: Examining how cultural factors influence AI acceptance and effectiveness in education.

Economic Analysis: Conducting comprehensive cost-benefit analyses of AI implementation in various educational contexts.

5. Conclusion

This comprehensive analysis of artificial intelligence in K-12 educational technology reveals both tremendous potential and significant challenges. The quantitative findings demonstrate that AI-powered educational tools can meaningfully improve learning outcomes, increase student engagement, and enhance educational efficiency. The observed effect sizes, particularly for struggling students, suggest that AI could play a crucial role in addressing persistent achievement gaps and personalizing education at scale.

However, the qualitative findings remind us that education is fundamentally a human endeavor that cannot be fully automated or algorithmatized. The concerns raised by stakeholders about equity, privacy, and the changing nature of teaching highlight the need for thoughtful, ethical implementation of AI in educational settings. The technology's potential can only be realized through careful integration that preserves the essential human elements of teaching and learning while leveraging AI's capabilities for personalization and efficiency.

The study's findings suggest that the future of AI in K-12 education lies not in replacement but in augmentation – creating AI-assisted learning environments where technology enhances human capabilities rather than supplanting them. This vision requires continued collaboration between educators, technologists, policymakers, and researchers to develop frameworks that maximize benefits while mitigating risks.

As we stand at the threshold of an AI-transformed educational landscape, the choices made today will shape the learning experiences of future generations. The evidence presented in this study supports cautious optimism about AI's role in education, provided that implementation is guided by pedagogical principles, ethical considerations, and an unwavering commitment to educational equity. The challenge ahead is not merely technical but fundamentally about reimagining education for the AI age while preserving its human essence.

The path forward requires continued research, thoughtful policy development, and most importantly, keeping student wellbeing and learning at the center of all decisions. As AI capabilities continue to evolve, so too must our understanding of how to harness these tools for the benefit of all learners. The future of education will likely be neither purely human nor purely artificial, but rather a carefully orchestrated synthesis that brings out the best of both worlds.

Conflict of interest: The authors declare no conflict of interest

Declaration of generative AI and AI-assisted technologies in the writing process: During the preparation of this work, the author(s) used AI tool, namely Claude and Gemini, in order to correct Grammatical mistakes and edit the language professionally. After using this tool/service, the author(s) reviewed and edited the content as needed.

ORCID

Yury Korolev https://orcid.org/0000-0001-8316-0058

Decision Impact Summary

This synthesis supports decisions by schools and teachers about selecting and using AI-enabled learning tools. The review and accompanying analysis suggest that, in many contexts, such tools can increase student engagement and retention, but effects depend on subject, cohort, and implementation choices. Schools should therefore frame adoption as a monitored trial: define target learners, specify the teaching decision the tool will support (for example, pacing or placement), and track learning outcomes, engagement, and subgroup equity against a teacher-designed baseline. Human oversight remains central–teachers retain control over recommendations, high-stakes actions require manual confirmation, and parents are informed about data use. The main risks are bias, over-automation, and privacy concerns for minors; these are best handled with simple equity checks, clear documentation for educators and families, and minimal, transparent data practices. The paper offers a practical map of applications and challenges and encourages sharing lightweight checklists and outcome-tracking templates so schools can evaluate impact responsibly.

References

1. Anderson, J. R., Corbett, A. T., Koedinger, K. R., & Pelletier, R. (1995). Cognitive Tutors: Lessons Learned. *Journal of the Learning Sciences, 4*(2), 167–207. DOI/Link

2. Baker, R. S. (2019). Challenges for the Future of Educational Data Mining: The Baker Learning Analytics Prizes. *Journal of Educational Data Mining, 11*(1), 1–17. DOI/Link

3. Baker, R. S., & Inventado, P. S. (2014). Educational Data Mining and Learning Analytics. In J. A. Larusson & B. White (Eds.), *Learning Analytics* (pp. 61–75). Springer. DOI/Link

4. Bloom, B. S. (1984). The 2 Sigma Problem: The Search for Methods of Group Instruction as Effective as One-to-One Tutoring. *Educational Researcher, 13*(6), 4–16. DOI/Link

5. Braun, V., & Clarke, V. (2006). Using Thematic Analysis in Psychology. *Qualitative Research in Psychology, 3*(2), 77–101. DOI/Link

6. Creswell, J. W., & Plano Clark, V. L. (2017). *Designing and Conducting Mixed Methods Research* (3rd ed.). SAGE. Link

7. Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly, 13*(3), 319–340. DOI/Link

8. Falmagne, J.-C., Albert, D., Doble, C. W., Eppstein, D., & Hu, X. (2013). *Knowledge Spaces: Applications in Education*. Springer. DOI/Link

9. Heffernan, N. T., & Heffernan, C. L. (2014). The ASSISTments Ecosystem: Building a Platform that Brings Scientists and Teachers Together for Minimally Invasive Research on Human Learning and Teaching. *International Journal of Artificial Intelligence in Education, 24*(4), 470–497. DOI/Link

10. Holmes, W., Bialik, M., & Fadel, C. (2019). *Artificial Intelligence in Education: Promises and Implications for Teaching and Learning*. Center for Curriculum Redesign. Link

11. Hwang, G.-J., Xie, H., Wah, B. W., & Gašević, D. (2020). Vision, Challenges, Roles and Research Issues of Artificial Intelligence in Education. *Computers & Education: Artificial Intelligence, 1*, 100001. DOI/Link

12. Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2016). *Intelligence Unleashed: An Argument for AI in Education*. Pearson. Link

13. 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), 901–918. DOI/Link

14. Moher, D., Liberati, A., Tetzlaff, J., & Altman, D. G. (2009). Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement. *PLOS Medicine, 6*(7), e1000097. DOI/Link

15. Pane, J. F., Steiner, E. D., Baird, M. D., Hamilton, L. S., & Pane, J. D. (2017). *Informing Progress: Insights on Personalized Learning Implementation and Effects*. RAND Corporation. DOI/Link

16. Piaget, J. (1952). *The Origins of Intelligence in Children*. International Universities Press. Link

17. Reich, J., & Mehta, J. (2020). Imagining September: Principles and Design Elements for Ambitious Schools During COVID-19. EdArXiv. DOI/Link

18. Reich, J., & Mehta, J. (2020). Imagining September: Online Design Charrettes for Fall 2020 Planning with Students and Stakeholders. EdArXiv. DOI/Link

19. Roschelle, J., Feng, M., Murphy, R. F., & Mason, C. A. (2016). Online Mathematics Homework Increases Student Achievement. *AERA Open, 2*(4), 1–12. DOI/Link

20. Selwyn, N. (2019). *Should Robots Replace Teachers? AI and the Future of Education*. Polity. Link

21. Settles, B., & Meeder, B. (2016). A Trainable Spaced Repetition Model for Language Learning. In *Proceedings of ACL 2016* (pp. 1848–1858). DOI/Link

22. Shermis, M. D., & Burstein, J. (Eds.). (2013). *Handbook of Automated Essay Evaluation: Current Applications and New Directions*. Routledge. Link

23. Suppes, P., & Morningstar, M. (1969). Computer-Assisted Instruction. *Science, 166*(3903), 343–350. DOI/Link

24. VanLehn, K. (2011). The Relative Effectiveness of Human Tutoring, Intelligent Tutoring Systems, and Other Tutoring Systems. *Educational Psychologist, 46*(4), 197–221. DOI/Link

25. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly, 27*(3), 425–478. DOI/Link

26. Vygotsky, L. S. (1978). *Mind in Society: The Development of Higher Psychological Processes*. Harvard University Press. Link

27. Walkington, C., & Bernacki, M. L. (2020). Appraising Research on Personalized Learning: Definitions, Theoretical Alignment, Advancements, and Future Directions. *Journal of Research on Technology in Education, 52*(3), 235–252. DOI/Link

28. 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*, 39. DOI/Link

29. Zeide, E. (2017). The Structural Consequences of Big Data-Driven Education. *Big Data, 5*(2), 164–172. DOI/Link