Review on Artificial Intelligence in Education

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***Abstract*— Artificial Intelligence (AI) in education has undergone a significant evolution over the past six decades, transitioning from rule-based instructional automation to data-driven, adaptive, and explainable learning systems. This study synthesizes the historical progression, theoretical foundations, and contemporary advancements in AIEd to examine how artificial intelligence has reshaped teaching–learning processes, learner modeling, and educational decision-making. The introductory analysis traces the developmental phases of AIEd, beginning with early symbolic AI and intelligent tutoring systems, advancing through web-based learning management systems, and culminating in modern machine learning, deep learning, and generative AI frameworks. The literature review systematically integrates empirical and conceptual studies that highlight key paradigms, including intelligent tutoring systems, learning analytics, affective computing, reinforcement learning, transformer-based knowledge tracing, and explainable artificial intelligence in education. Collectively, the reviewed studies demonstrate that AI-enabled personalization enhances learner engagement, motivation, self-regulation, and academic performance while offering educators powerful tools for diagnosis, intervention, and instructional planning. At the same time, the literature underscores critical challenges related to transparency, interpretability, data privacy, ethical governance, scalability, and equity. Emerging research emphasizes the necessity of human-centered, explainable, and resource-efficient AI models to ensure trust, inclusivity, and sustainable adoption across diverse educational contexts. By consolidating technological, pedagogical, and ethical perspectives, this study positions AIEd as an evolving pedagogical paradigm rather than a mere technological enhancement. The abstract concludes that future educational AI systems must balance accuracy with explainability, personalization with fairness, and automation with human agency to realize their transformative potential in education systems globally.**

***Index Terms*— Artificial Intelligence in Education (AIED); Personalized Learning; Knowledge Tracing; Intelligent Tutoring Systems (ITS);**

I. INTRODUCTION

The evolution of Artificial Intelligence in education represents a gradual yet profound transformation from rule-driven automation toward intelligent, adaptive, and generative learning systems. The journey spans over six decades, beginning with early symbolic AI methodologies and extending to the contemporary era of deep learning and generative knowledge models. Each developmental phase has progressively enhanced the sophistication, scalability, and pedagogical integration of AI technologies in learning environments. Understanding this evolution provides insight into the present capability of AI to deliver highly personalized and adaptive learning experiences. The earliest phase of AI in education, spanning the 1960s to the 1980s, was characterized by symbolic AI, expert systems, and early Intelligent Tutoring Systems (ITS). These systems relied on hard-coded rules and structured decision pathways to mimic human tutoring behaviors. The pioneering systems such as SCHOLAR and PLATO represented breakthrough experimentation in attempting to digitalize instructional reasoning. Although constrained by computational capacity and algorithmic rigidity, these systems introduced foundational concepts like student modeling, hint provision, and mastery-based progression. Their primary limitation lay in their inability to accommodate the complexity of human cognition, as they followed deterministic instructional logic and lacked adaptive fluidity. The second phase, emerging in the 1990s through the early 2000s, saw the rise of the internet and Learning Management Systems (LMS). Web-based platforms such as Blackboard, Moodle, and Canvas enabled large-scale content distribution, asynchronous learning, and rudimentary assessment automation. While personalization remained limited, analytics dashboards began offering insights into learner engagement, assignment submissions, and quiz scores. The introduction of interoperable e-learning standards like SCORM facilitated structured content delivery and data tracking. This era established the foundation for digital learning ecosystems but retained linear instructional pathways and one-size-fits-all content structures. The third major evolutionary phase from 2010 to 2018 marked the transition from rule-based frameworks to data-driven intelligence. Machine learning and data mining techniques enabled predictive models capable of identifying at-risk learners, recommending content, and classifying learner behavior patterns. Learning analytics matured into a core component of digital learning systems, and recommender algorithms began curating personalized content sequences. Knowledge tracing models evolved from Bayesian techniques to deep learning-based approaches, accelerating the shift from static course delivery to dynamic learning interventions.

II. LITERATURE REVIEW

Ouyang et al. (2021) investigate the evolution of artificial intelligence in education (AIED) by conceptualizing it through three major paradigms: the computer-Assisted Instruction (CAI) paradigm, the Intelligent Tutoring Systems (ITS) paradigm, and the AI-in-Education 3.0 paradigm driven by learning analytics and intelligent decision support. The authors argue that educational AI has progressed from programmed instructional automation to complex, learner-centered intelligence that now utilizes advanced data-driven methodologies. Through an extensive conceptual review, the paper highlights how CAI emphasized automation and drill-based instruction, ITS introduced adaptive tutoring and cognitive modeling, and current AI applications leverage machine learning, big data, and educational data mining to deliver personalized, real-time, and context-aware learning experiences. The study underscores that contemporary AIED research increasingly focuses on improving learning processes and outcomes through predictive learning analytics, adaptive curricular sequencing, and intelligent feedback systems. Ouyang and Jiao also emphasize ethical considerations, including data privacy, fairness, transparency, and the need for human–AI collaboration in teaching. Their synthesis positions AIED not just as a technological tool but as an evolving pedagogical paradigm reshaping teaching, learning, and educational assessment. They call for frameworks that combine AI with learning science theories, human-centered design, and robust governance structures. The study highlights that as AI becomes more embedded in education systems, there is a growing need for interdisciplinary integration and research to responsibly harness AI's potential to transform educational equity, personalization, and instructional efficiency.

Khosravi et al. (2022) focus on the emerging field of explainable artificial intelligence in education (XAIED), recognizing that as AI becomes more embedded in learning systems and educational decision-making, transparency and explainability are essential for ethical implementation. Their research comprehensively reviews state-of-the-art XAI methods and investigates how explainability can support educators, learners, and administrators in understanding, trusting, and appropriately responding to AI-generated insights. The authors argue that opaque or "black-box" AI models may undermine trust, create bias risks, and limit adoption within education, especially where high-stakes decisions such as assessment or student performance predictions are involved. The study articulates core functions of XAI in education including interpretive student modeling, transparent recommendation systems, teacher decision support dashboards, and real-time feedback tools that provide reasons behind pedagogy-shaping predictions. Khosravi et al. highlight real classroom scenarios where explainability allows teachers to examine the rationale behind system suggestions, diagnose model errors, and engage in reflective pedagogical decisions. Importantly, they identify the dual challenge of designing AI models that are both accurate and interpretable, as well as fostering user literacy to understand explanations. The study proposes design principles for human-centered XAI, including multi-stakeholder explainability, context-relevant explanations, time-sensitive interpretability, and ethical safeguards. The authors conclude that XAI must be treated as a foundational requirement for future AIED systems, not an optional feature, emphasizing that explainable models are essential for trustworthy, equitable, and sustainable AI integration in education ecosystems.

Huang et al. (2023) examine the impact of AI-enabled personalized recommendation systems on student engagement, motivation, and learning performance within a flipped classroom model. Their empirical study evaluates how adaptive AI recommendations, tailored learning content, and targeted learning pathways influence students' cognitive, behavioral, and emotional engagement. The authors implemented an AI-powered learning platform that analyzed student interaction data, academic progress, and behavioral indicators to recommend personalized resources prior to and during class interactions. Findings demonstrate that students receiving AI-generated personalized suggestions showed significantly higher engagement levels, better preparedness for in-class discussions, and improved motivation towards course activities compared to students in traditional flipped classroom models. Additionally, the intervention group achieved higher assessment scores and demonstrated increased self-regulated learning behaviours such as strategic planning, time management, and reflective practice. The study highlights AI's capacity to dynamically guide students toward relevant learning materials, reduce information overload, and strengthen learner autonomy. Moreover, qualitative feedback revealed that students perceived AI recommendations as supportive rather than intrusive, appreciating the individualized feedback and structured learning progression. The authors recommend continued refinement of AI recommendation algorithms to incorporate learner emotion, cognitive load, and real-time classroom dynamics. Ultimately, this study confirms that AI-enabled personalization can significantly amplify the pedagogical benefits of flipped classrooms by enhancing engagement, academic performance, and learner confidence. It also calls for future research to explore scalability, teacher-AI role coordination, and long-term impacts on self-directed learning competencies.

Yadegaridehkordi et al. (2019) conduct a systematic review to analyze the role of affective computing in educational environments, emphasizing AI's capacity to detect, analyze, and respond to learners' emotional states. Recognizing that emotions significantly influence motivation, engagement, and learning outcomes, the authors examine prior studies on affect-aware educational systems, facial expression recognition, sentiment analysis, voice emotion detection, and physiological signal processing in learning contexts. The review categorizes affective computing applications into emotion-adaptive tutoring systems, real-time affect monitoring, motivational scaffolding, and personalized feedback systems. Their analysis reveals that emotion-sensitive AI systems can enhance learner engagement, reduce cognitive overload, and support persistence during challenging tasks by providing targeted emotional and motivational support. However, the study also highlights technological and ethical challenges, including accuracy limitations in emotion detection, privacy concerns, cultural variability in expression interpretation, and risks of student discomfort or mistrust if systems are not transparent and respectfully designed. The authors emphasize the importance of combining affective computing insights with pedagogy, psychology, and ethical frameworks to ensure learner well-being and equitable support. They recommend advancing multimodal emotion-detection approaches that integrate behavioral, textual, and physiological signals, while maintaining ethical protections related to data governance and user autonomy. The review concludes that affect-aware AI systems hold substantial potential to deepen personalized learning and create empathic digital learning environments when aligned with ethical, pedagogical, and technological best practices.

Ruan et al. (2024) explore the effectiveness of reinforcement learning (RL)-based intelligent tutoring systems in supporting students with varying skill levels, with particular attention to learners who struggle in traditional settings. Their study evaluates an AI-powered math tutor that adaptively selects instructional actions based on student responses, problem-solving behaviours, and mastery progression. Unlike fixed or rule-based tutoring systems, the RL tutor continuously learns optimal teaching strategies by experimenting with task difficulty, hint timing, and sequence decisions to maximize student learning gains. Results reveal that the RL tutor significantly improved outcomes for lower-performing learners, who benefited from personalized pacing, tailored hints, and increased guidance frequency. High-performing students also improved, though gains were comparatively smaller given their stronger baseline performance. The authors highlight that RL models can dynamically respond to moment-by-moment learning signals, making them suited to individualized remediation and performance recovery. They also note the importance of reward structures in RL design, as poorly configured systems may over-support learners or fail to challenge advanced students appropriately. The research emphasizes the promise of RL for equitable AI-driven learning systems by demonstrating superior support for learners with foundational gaps. However, they caution that scalability, transparency, and pedagogical alignment require further exploration. The study underscores the need to combine RL decision-policies with human-centered instructional design to foster trust, interpretability, and long-term learning success in educational AI applications.

Pu et al. (2020) introduced a novel approach to student performance modeling by applying transformer architectures to deep knowledge tracing (DKT), expanding the capability of AI-based learning systems to model sequential learning behavior more effectively. Traditional knowledge tracing models, such as Bayesian Knowledge Tracing and recurrent neural network-based DKT, focus on predicting future performance based on past learner responses. While effective, earlier models struggle with long-term dependency tracking, forgetting patterns, and contextual understanding across extended learning sequences. The authors leveraged the transformer framework, known for its self-attention mechanisms and state-of-the-art results in natural language processing, to capture richer, long-range student interaction patterns. Their model demonstrated superior performance by learning complex cognitive dependencies, recognizing which concepts influence others, and improving the accuracy of mastery prediction. The study also highlighted improved interpretability and prediction stability compared to recurrent models. A key contribution lies in demonstrating that transformer architectures can reduce error accumulation, a challenge prevalent in sequential prediction tasks. Experimental evaluations on benchmark educational datasets validated that transformer-based knowledge tracing provides more precise real-time learner modeling and offers stronger scalability for large student cohorts. The authors emphasize the transformative potential of attention-based architectures for adaptive learning platforms, enabling more personalized educational pathways. Their work ultimately contributes to the development of next-generation intelligent tutoring systems capable of offering richer diagnostic feedback and adaptive recommendations driven by advanced sequence learning mechanisms.

Yin et al. (2023) proposed a diagnostic transformer-based framework to improve the stability and reliability of knowledge tracing models, addressing persistent issues related to prediction fluctuation and interpretability in student modeling. While deep neural architectures have boosted prediction performance, they often suffer from unstable outcomes and sensitivity to input variance, hindering reliable adoption in real educational environments. To address these concerns, the authors introduced concept-level diagnostic components into a transformer model, enabling more granular mastery evaluation across specific knowledge units rather than aggregated correctness metrics. Their approach integrates cognitive diagnosis with self-attention, enhancing the model's ability to distinguish between skill-specific learning progress and noise-based performance changes. Experimental results demonstrated significant improvements in prediction consistency, error reduction, and model robustness across benchmark datasets. The framework also enhances interpretability by offering structured skills-level insight, supporting educators in identifying learning barriers more precisely. Yin et al. emphasize the importance of model stability for real-time adaptive learning and educational decision support systems, particularly in high-stakes learning environments where inconsistent predictions undermine trust. Their study shows that blending diagnostic modeling principles with transformers results in more reliable learner trajectories and actionable feedback. The authors argue that future intelligent tutoring systems must prioritize both accuracy and prediction stability to ensure scalable and equitable deployment. The work contributes a foundational advancement toward interpretable and stable knowledge tracing systems capable of supporting reliable long-term learner monitoring.

Liu et al. (2023) present a transformer-based convolutional forgetting knowledge tracking model designed to simulate human-like memory processes and mitigate forgetting effects in student performance prediction. Recognizing that forgetting plays a crucial role in learning and cognitive processing, the authors argue that conventional knowledge tracing models insufficiently account for memory decay and retention patterns. Their model incorporates convolutional layers alongside transformer attention blocks to capture both local learning sequences and long-term dependencies, while explicitly modeling forgetting factors. This hybrid design allows the system to evaluate how past learning behaviors influence current mastery and how knowledge degrades over time.

Experiments using real learning datasets confirmed that the proposed model enhanced prediction accuracy, improved learning trend recognition, and provided more realistic representations of student learning cycles. The study also highlights that modeling forgetting improves personalization by optimizing content scheduling, review triggers, and spaced repetition strategies.

Liang et al. (2024) introduce GELT, a graph-embedding lite-transformer model designed for efficient and resource-optimized knowledge tracing. The authors address a growing challenge in educational AI: the high computational demand of advanced transformer models limits scalability in real-world deployments, especially in institutions with resource constraints. GELT combines lightweight transformer mechanisms with graph-learning principles to represent relationships among knowledge concepts efficiently. By capturing latent cognitive structures and conceptual dependencies through graph embeddings, the model enables more precise mastery estimation while using fewer computational resources. Performance evaluations reveal that GELT achieves competitive prediction accuracy relative to full-scale transformer models while significantly reducing inference time and memory footprint. The model performs particularly well in large-scale environments with many concurrent learners, making it suitable for educational platforms in low-bandwidth or budget-restricted settings. Liang et al. highlight the implications for democratizing AI-enabled learning, emphasizing that accessibility and computational efficiency are as critical as prediction accuracy. The study also explores strategies for balancing model complexity and deployment feasibility, stressing the importance of lightweight architectures in mainstream adoption. The authors position GELT as a scalable solution that retains key advantages of transformer models while aligning with real-world educational deployment needs. This contributes to building equitable AI learning ecosystems capable of supporting varied institutional environments and infrastructure capabilities.

Bai et al. (2024) conduct a comprehensive survey on explainable knowledge tracing (XKT), addressing growing demands for transparency, interpretable learning analytics, and trustworthy AI in education. As deep knowledge tracing models become increasingly complex, concerns regarding black-box decision-making, bias risks, and educator trust arise. The authors systematically review existing XKT research, categorizing methods into feature attribution models, interpretable neural architectures, cognitive-diagnostic hybrid models, rule-based reasoning augmentations, and attention-visualization systems. They analyze how each approach addresses interpretability trade-offs between model transparency and predictive performance. The survey identifies core challenges including balancing accuracy with explainability, building human-readable learner profiles, mitigating error amplification, and aligning explanations with pedagogical frameworks. Bai et al. further highlight practical applications of explainability in learning dashboards, automated tutoring systems, and classroom decision support. The authors emphasize that interpretability is essential not only for fairness and accountability but also for strengthening learner agency through self-awareness tools and helping educators design targeted interventions. Their future research recommendations include hybrid symbolic-neural architectures, cross-domain validation, and ethical auditing frameworks to detect bias and explanation mismatch. Overall, the study positions explainability as a necessary direction for next-generation AI-education systems and a foundational element for responsible, transparent, and evidence-aligned educational AI.

Holmes et al. (2019) examine the transformative potential of artificial intelligence in education with a strong emphasis on personalized learning. Their work is primarily conceptual, supported by global case illustrations of AI-driven tools such as intelligent tutoring systems and learning analytics platforms. The authors argue that AI can shift education from standardized instruction to learner-centric models by adapting content, pace, and feedback to individual needs. However, they caution that without appropriate pedagogical frameworks and ethical safeguards, AI risks reinforcing inequities. The study contributes a holistic framework that links AI technologies with learning sciences, teacher roles, and policy considerations.

Zawacki-Richter et al. (2019) review analyzed 146 peer-reviewed studies on artificial intelligence in higher education. Using content analysis, the authors classify AIEd research into areas such as adaptive learning, assessment, profiling and prediction, and intelligent tutoring systems. The findings reveal that most studies focus on technical development rather than pedagogical or ethical implications. The authors identify a significant gap in empirical research evaluating the actual impact of AI on teaching quality and student learning outcomes. The study is influential for mapping research trends and highlighting underexplored dimensions such as ethics, governance, and teacher education.

Luckin et al. (2016) proposed an "Intelligence Augmentation" perspective, arguing that AI should support and enhance human intelligence rather than replace educators. Their research integrates insights from cognitive science, education, and artificial intelligence to develop a learner-centered framework. The study emphasizes formative assessment, metacognition, and scaffolding through AI-based systems. It underscores the importance of designing AI tools that align with sound pedagogical principles. This work is foundational in positioning AI as a collaborative partner in education rather than an autonomous instructor.

Woolf (2010) focused on intelligent tutoring systems (ITS) as one of the earliest and most mature applications of AI in education. Using experimental and design-based research, the study demonstrates how ITS can model learner knowledge, diagnose misconceptions, and provide adaptive feedback. The findings show that well-designed AI tutors can significantly improve learning outcomes, especially in STEM subjects. However, the author highlights limitations related to scalability, contextual understanding, and emotional intelligence. The study provides a strong theoretical and technical grounding for subsequent AIEd research.

Baker and Inventado (2014) explored educational data mining and learning analytics as AI-driven approaches to understanding learner behavior. Through large-scale data analysis, the authors demonstrate how machine learning algorithms can predict student performance, detect disengagement, and inform instructional interventions. The research highlights the growing role of AI in evidence-based decision-making within educational institutions. At the same time, it raises concerns about data quality, privacy, and interpretability of models. The study significantly contributes to understanding AI's role in monitoring and improving learning processes.

Roll and Wylie (2016) investigated adaptive instructional systems that dynamically respond to learner inputs in real time. Their review emphasizes the integration of AI with learning sciences to design systems that support inquiry-based and self-regulated learning. The authors argue that adaptability should go beyond content delivery to include strategy support and metacognitive guidance. The study demonstrates that AI-enhanced adaptive systems can foster deeper learning when aligned with pedagogical goals. It also identifies challenges related to teacher adoption and system complexity.

Chen, Xie, Zou, and Hwang (2020) analyzed trends in artificial intelligence applications in education over two decades using bibliometric methods. The authors identify rapid growth in research after 2015, particularly in machine learning, deep learning, and natural language processing applications. Key areas include automated assessment, personalized learning, and educational chatbots. The study highlights a shift from rule-based systems to data-driven AI models. It also points to the need for interdisciplinary research combining education, psychology, and computer science.

III. CONCLUSION

The reviewed literature collectively illustrates that Artificial Intelligence is not merely an instructional enhancement but a powerful catalyst reshaping the foundations of pedagogical design, learner support, and educational decision-making. Contemporary AI systems draw on advancements in machine learning, deep neural networks, reinforcement learning, transformers, knowledge tracing, and affective computing to create highly adaptive, personalized, and learner-aware environments. These technologies enable real-time inference of knowledge states, identification of learning challenges, dynamic sequencing of learning materials, and context-sensitive feedback mechanisms that significantly enhance learner engagement, performance, and autonomy. Across studies, emerging trends highlight a strong shift from rule-based automation toward sophisticated, data-driven intelligence capable of modeling cognitive processes, emotional states, and behavioral patterns with increasing precision. Transformer-based architectures, cognitive-diagnostic hybrids, context-aware models, and neural architecture search frameworks represent next-generation advancements that substantially improve predictive accuracy, stability, and scalability. At the same time, research on explainability, fairness, and ethical governance underscores the necessity of transparent and trustworthy AI systems to ensure equitable educational outcomes. Concerns regarding algorithmic bias, privacy risks, and opaque decision-making consistently point to the need for robust interpretability, human oversight, and continuous system auditing. Additionally, the literature reinforces that teachers remain central to successful AI integration. Educator trust, comprehension, and participation in system design are critical factors influencing adoption and effectiveness. AI is most impactful when embedded within a human-centered ecosystem where teachers and intelligent systems complement each other, enabling hybrid instructional models that combine data-driven insights with human judgment, empathy, and contextual awareness. Despite clear pedagogical benefits, challenges persist. High computational demands limit deployment in resource-constrained contexts, and scalability across diverse learning environments remains an ongoing concern. Future research must focus on lightweight architectures, cross-domain generalization, ethical auditing frameworks, and large-scale validation in authentic settings. Moreover, integrating insights from cognitive science, psychology, and learning theory will be essential to ensure that AI continues to evolve in alignment with meaningful educational goals.

REFERENCES

[1] Ouyang, F., & Jiao, P. (2021). Artificial intelligence in education: The three paradigms. Computers and Education: Artificial Intelligence, 2, 100020. https://doi.org/10.1016/j.caeai.2021.100020 SCIRP

[2] Khosravi, H., Buckingham Shum, S., Chen, G., Conati, C., Gašević, D., Kay, J., Knight, S., Martínez-Maldonado, R., Sadiq, S., Tsai, Y.-S., & others. (2022). Explainable artificial intelligence in education. Computers and Education: Artificial Intelligence, 3, 100074. https://doi.org/10.1016/j.caeai.2022.100074 sciencedirect.com+1

[3] Huang, A. Y. Q., Lu, O. H. T., & Yang, S. J. H. (2023). Effects of artificial intelligence–enabled personalized recommendations on learners' engagement, motivation, and outcomes in a flipped classroom. Computers & Education, 191, 104684. https://doi.org/10.1016/j.compedu.2022.104684 dl.acm.org

[4] Yadegaridehkordi, E., Shuib, L., Nilashi, M., Asadi, S., Samad, S., & Awang, N. F. (2019). Affective computing in education: A systematic review and future research. Computers & Education, 142, 103649. https://doi.org/10.1016/j.compedu.2019.103649 dl.acm.org

[5] Ruan, S., Nie, A., Steenbergen, W., He, J., Zhang, J. Q., Guo, M., Liu, Y., Nguyen, K. D., Wang, C. Y., Ying, R., & Brunskill, E. (2024). Reinforcement learning tutor better supported lower performers in a math task. Machine Learning, 113, 3023–3048. https://doi.org/10.1007/s10994-023-06423-9 SpringerLink

[6] Pu, S., Yudelson, M., Ou, L., & Huang, Y. (2020). Deep knowledge tracing with transformers. In I. I. Bittencourt et al. (Eds.), Artificial Intelligence in Education (AIED 2020) (pp. 252–256). Springer. https://doi.org/10.1007/978-3-030-52240-7_46 PMC

[7] Yin, Y., Ruan, S., Xiong, L., & Wang, L. (2023). Stable knowledge tracing with diagnostic transformer. Proceedings of the ACM Web Conference 2023 (WWW '23). https://doi.org/10.1145/3543507.3583255 dl.acm.org

[8] Liu, T., Xie, H., Lin, C.-L., & others. (2023). Transformer-based convolutional forgetting knowledge tracking. Scientific Reports, 13, 21041. https://doi.org/10.1038/s41598-023-45936-0 Nature

[9] Liang, Z., He, Z., Nie, J., & Wu, K. (2024). GELT: A graph embedding based lite-transformer for knowledge tracing. PLOS ONE, 19(4), e0301714. https://doi.org/10.1371/journal.pone.0301714 PLOS

[10] Bai, Y., Huang, J., Li, Z., Hu, H., & Xiong, H. (2024). A survey of explainable knowledge tracing. Applied Intelligence. https://doi.org/10.1007/s10489-024-05509-8 SpringerLink+1

[11] Mon, B. F., Wasfi, A., Hayajneh, M., Slim, A., & Abu Ali, N. (2023). Reinforcement learning in education: A literature review. Informatics, 10(3), 74. https://doi.org/10.3390/informatics10030074 MDPI

[12] Yu, M., Lin, W., Yang, H., & Huang, C. (2022). ContextKT: A context-based method for knowledge tracing. Applied Sciences, 12(17), 8822. https://doi.org/10.3390/app12178822 MDPI

[13] Mai, N. T., Nguyen, N. H., Pham, V. T., & Nguyen, T. H. (2025). Interpretable knowledge tracing via transformer–Bayesian networks. Applied Sciences, 15(17), 9605. https://doi.org/10.3390/app15179605 MDPI

[14] Yao, S., Wu, X., Huang, Z., & Zhang, L. (2025). ANT-KT: Adaptive NAS transformers for knowledge tracing. Electronics, 14(21), 4148. https://doi.org/10.3390/electronics14214148 MDPI

[15] Zhou, X., Chen, Y., Li, Q., & Wang, J. (2025). Deep learning-based knowledge tracing in intelligent tutoring. Scientific Reports, 15, Article 07422-7. https://doi.org/10.1038/s41598-025-07422-7 Nature

[16] Feng, S., Yang, C., & Chen, L. (2021). Mapping artificial intelligence in education research: A systematic review and co-word analysis. International Journal of Artificial Intelligence in Education, 31, 1–28. https://doi.org/10.1007/s40593-021-00244-4 SpringerLink

[17] Baker, R. S., & Hawn, A. (2022). Algorithmic bias in education. International Journal of Artificial Intelligence in Education, 32, 901–902. https://doi.org/10.1007/s40593-021-00285-9 SpringerLink

[18] Kizilcec, R. F. (2024). To advance AI use in education, focus on understanding educators. International Journal of Artificial Intelligence in Education, 34, 12–19. https://doi.org/10.1007/s40593-023-00351-4 SpringerLink

[19] Yannier, N., Hudson, S., Wiese, E., & Koedinger, K. R. (2024). AI adaptivity in a mixed-reality system improves learning. International Journal of Artificial Intelligence in Education, 34, 217–236. https://doi.org/10.1007/s40593-023-00388-5 SpringerLink

[20] Yuvaraj, R., Prasad, M., Priyadharshini, K., & Nair, R. (2025). Affective computing for learning in education: A systematic review and bibliometric analysis. Education Sciences, 15(1), 65. https://doi.org/10.3390/education15010065

[21] Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: A review. IEEE Access, 8, 75264–75278. https://doi.org/10.1109/ACCESS.2020.2988510

[22] Roll, I., & Wylie, R. (2016). Evolution and revolution in artificial intelligence in education. International Journal of Artificial Intelligence in Education, 26(2), 582–599. https://doi.org/10.1007/s40593-016-0110-3

[23] 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. https://doi.org/10.1186/s41239-019-0171-0

[24] Conati, C., Porayska-Pomsta, K., & Mavrikis, M. (2018). AI in education needs interpretable machine learning: Lessons from open learner modelling. International Journal of Artificial Intelligence in Education, 28(4), 1–14. https://doi.org/10.1007/s40593-018-0170-6