1a: How can AI personalize learning experiences for individual students?

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The integration of Artificial Intelligence (AI) into education holds transformative potential for personalizing learning experiences. This literature review examines various facets of AI's role in tailoring education to individual student needs, drawing upon a diverse body of research.

Several studies highlight the effectiveness of AI in adapting content delivery and learning modalities. Do et al. (2024) found that personalized AI-generated podcasts, tailored to student majors, interests, and learning styles, led to significantly improved learning outcomes compared to traditional textbooks. Similarly, Baillifard et al. (2023) demonstrated the efficacy of AI tutors in implementing personalized retrieval practice, resulting in higher grades for students who actively engaged with the AI tutor. This aligns with the findings of Kolluru et al. (2018), who showcased AI's ability to enrich learning experiences by dynamically adjusting content based on learner feedback, using clustering algorithms and recommender systems. Complementing these findings, Cui et al. (2019) demonstrated the superior performance of the Yixue Squirrel AI adaptive learning system compared to both traditional classroom instruction and another adaptive learning platform. These adaptive systems, as explored by Strielkowski et al. (2024), are transforming education by tailoring lessons to individual needs and abilities, a shift further explored by Akavova et al. (2023) who reviewed the use of AI in personalized feedback and adaptation in education. The potential for personalized, immersive learning is further explored by Kamruzzaman et al. (2023), demonstrating the role of AI and IoT in creating dynamic and responsive educational environments even during pandemics.

Beyond content adaptation, AI can personalize learning through intelligent feedback and support. Mollick and Mollick (2024) explored how instructors can leverage generative AI to create personalized learning experiences, offering prompts and blueprints for AI-based exercises in simulations, mentoring, and co-creation. Nazaretsky et al. (2022) found that an AI-powered learning analytics tool, co-designed with teachers, improved their ability to plan personalized learning sequences. This resonates with the work of Xiong et al. (2024), who reviewed recent advancements in personalized educational data mining, including educational recommendation, cognitive diagnosis, knowledge tracing, and learning analysis. Furthermore, RIZVI (2023) assessed the potential of

AI-powered tutoring systems for personalized guidance, highlighting the role of algorithms like machine learning and data mining in tailoring interactions to individual student needs. Complementing this perspective, Sajja et al. (2023) proposed the AIIA framework, an AI-powered intelligent assistant for personalized and adaptive learning, demonstrating its potential to reduce cognitive load and offer tailored support.

AI also plays a role in understanding individual learner profiles. Liu (2020) proposed a model for learning personalized conversational embeddings from dyadic conversations, demonstrating improved personality inference accuracy. Similarly, Ramon et al. (2021) explored how explainable AI can be used to validate and improve models that classify psychological traits from digital footprints. This echoes the work of Omelianenko (2017), who used deep machine learning for psycho-demographic profiling to enhance AI systems' understanding of humans. These findings are crucial for tailoring educational interventions to individual learning styles and preferences, as emphasized by Takamido et al. (2024) who used neural Granger causality to understand inter-personal coordination dynamics. Furthermore, Kutt et al. (2020) developed a personalized emotion response model considering individual personality differences, highlighting the importance of personalized models in AI. This work aligns with Yu et al. (2024) who examined the effectiveness of AI directors in personalizing the gaming experience based on player preference.

The personalization facilitated by AI extends to various educational contexts and challenges. Daskalaki et al. (2024) surveyed educators across multiple countries and found cautious optimism regarding AI in education, particularly for personalized learning, while also highlighting the need for professional development. Similarly, Wang et al. (2023) investigated the impact of AI applications on international students, exploring personalized learning, adaptive testing, and predictive analytics, while addressing concerns like privacy and cultural differences. This focus on personalized support aligns with the work of Ghafghazi et al. (2021), who developed an AI-augmented platform for personalized treatment and learning plans for individuals with autism spectrum disorder. These efforts extend to addressing challenges in specific subjects, such as math anxiety, as explored by Inoferio et al. (2024), who found that AI models can serve as "mentors" and "math companions," providing personalized support and reducing anxiety. Further, Niu et al. (2022) investigated the use of an AI-aided educational platform in less developed areas of China, finding that it provided valuable resources and personalized learning opportunities.

Several researchers have investigated the role of AI in specific learning scenarios and tools. Jadeja and Varia (2017) discussed personalization in conversational AI systems and highlighted its importance in enhancing user experience. Shih et al. (2017)

demonstrated how a hybrid brain-computer interface can provide implicit reinforcement to an AI agent, adapting AI behavior to individual preferences. This aligns with the work of Zeng et al. (2022), who developed an interactive platform for human-in-the-loop reinforcement learning, enabling users to manipulate task difficulty and provide curriculum feedback. Similar approaches are seen in Bhatt et al. (2023), who developed a tool to learn personalized decision support policies. Further emphasizing personalized feedback, Cha et al. (2018) developed a system for augmenting neuropsychological assessments using AI, providing quantitative results and visualizations for neuropsychologists.

The impact of AI on diverse learning modalities and specific skills has also been examined. Kim and Kim (2024) explored the use of AI in creating personalized experiences in virtual reality art, while Kim et al. (2024) developed an AI-powered tool for generating personalized translations of scientific text. Addressing the needs of specific learners, Lyu et al. (2024) designed a social-emotional game for children with autism spectrum disorder, using AI to generate personalized stories. This personalized approach extends to language learning, with Konyrova (2024) exploring the impact of AI on ESL instruction and how it enhances language learning outcomes. Further, Moybeka et al. (2023) explored how AI affects EFL students' motivation, suggesting that AI can boost self-efficacy and facilitate personalized learning.

Personalized learning is further enhanced by considerations of learning styles and individual preferences. Yu et al. (2024) demonstrated the effectiveness of non-random AI directors in personalizing quest selection in video games. Hrnjic and Tomczak (2019) explored how machine learning can support behavioral economics in designing personalized interventions. Furthermore, Ai et al. (2019) examined the effect of personalization on product search, proposing a zero attention model for personalized product retrieval. This emphasis on personalization is crucial in human-computer interaction, as discussed by Richardson et al. (2023), who proposed a summary-augmented approach for personalized language model outputs.

Addressing the practical and ethical considerations of AI in education is also essential. Alkaeed et al. (2023) explored privacy challenges in the metaverse and discussed technical solutions like differential privacy and federated learning. Cao et al. (2022) proposed a federated learning method for personalized model training, allowing clients to design their own models without sharing architecture information. This aligns with Heo et al. (2023), who extended DP-SGD to support personalized differential privacy in deep learning. Furthermore, Poretschkin et al. (2023) discussed the trustworthiness of AI applications and the need for clear quality criteria, while Kuhl et al. (2020) investigated the role of personalized AI explanations in influencing compliance behavior.

AI's transformative potential extends to various learning contexts. Shi et al. (2024) developed an open-source learning module for building robot companions, emphasizing human-centered AI and personalized learning experiences. Chan and Tsi (2023) explored the potential of AI in higher education, emphasizing the importance of human teachers and proposing a roadmap for integrating AI effectively. Kuo et al. (2024) introduced generative AI models to enhance deep knowledge tracing for personalized adaptive learning, addressing data scarcity issues. This focus on data-driven personalization is also seen in Ramakrishnan et al. (2023), who reviewed AI applications in healthcare, particularly AI-driven recommender systems in nutrition. These advancements contribute to a future of personalized recommendations for healthier lifestyles.

Further exploring the diverse applications of AI in education, Ahmad and Haddad (2024) used deep learning models to predict thyroid cancer recurrence, demonstrating the potential of AI for personalized treatment approaches. Khamoushi (2024) compared traditional and AI-driven food marketing techniques, highlighting AI's ability to personalize campaigns. Hao et al. (2023) introduced the concept of SAISSE, promoting symbiotic AI-human relationships through shared sensory experiences. Wynn et al. (2023) investigated how representational alignment between humans and AI agents influences the learning of human values. Morla (2019) discussed ten key issues in cybersecurity related to AI, while Yan et al. (2024) explored the use of generative AI in social life simulation for non-cognitive skills learning. Rismani et al. (2024) adapted System Theoretic Process Analysis for analyzing AI operation and development processes. Baltezarević and Baltezarević (2024) explored students' attitudes toward AI in personalized learning, finding positive perceptions regarding AI's ability to enhance learning and address individual needs. Kretzschmar et al. (2024) found that an AI learning assistant significantly improved performance results for students in an advanced math course. Shete et al. (2024) investigated the impact of AI-driven personalization on learners' performance, finding a positive correlation between AI-driven personalized learning and academic achievement. Abu Khurma et al. (2024) assessed the measurement of student engagement dimensions within AI ChatGPT interactions. Mutambik (2024) explored how AI-powered automation can enhance student learning experiences in Saudi Arabia as a pathway for sustainable education.

Continuing the exploration of AI in various educational contexts, Abimbola and Sulaimon (2024) examined AI-driven pedagogical strategies for improving equitable access to science education, highlighting AI's potential for personalized learning and real-time feedback. Luo (2024) introduced the ACEM, an AI-driven framework for personalized cognitive development. Junior et al. (2024) explored the use of AI to personalize learning based on brain functions. Oseremi Onesi-Ozigagun et al. (2024) reviewed how AI is revolutionizing education by personalizing learning experiences and transforming teaching methodologies. Hasibuan and Azizah (2023) investigated the use of AI to personalize learning and encourage creativity. Altaleb et al. (2023) designed an Adaptive Learning Platform (ALP) based on AI algorithms for personalized course learning paths. Yang et al. (2023) explored how technology can support dynamic transitions between individual and collaborative learning activities. González et al. (2022) proposed using an AI virtual assistant and a recommender system to leverage collective knowledge and enhance learning experiences for software engineering students. Sajadi et al. (2023) explored the use of generative AI to create individual performance summaries based on peer evaluations. Riedl and Bogert (2024) investigated how AI feedback affects learning, skill gap, and diversity of decision strategies. Taheri et al. (2024) proposed a method for enriching interactions with conversational AI for individuals with neuromuscular diseases. Thuy An Ngo et al. (2024) studied the factors influencing student satisfaction and continued usage of ChatGPT in an educational context. Zikra and Suvaid (2023) explored the impact of Google's Bard and OpenAI's ChatGPT on personalized learning experiences. Teresa et al. (2023) demonstrated the effectiveness of AI in creating interactive and personalized learning experiences for children through videos. Albdrani and Al-Shargabi (2023) investigated the use of ChatGPT in providing personalized learning experiences for data science education. Mohammad Mazedul Huq Talukdar (2023) examined the factors influencing students' willingness to participate in AI education at the Higher Secondary School level. Кузьмин et al. (2024) explored the use of AI for building individual learning trajectories in universities. Cairo and Echavarría (2023) analyzed the impact of intelligent tutoring systems on the quality of higher education based on AI. Rane (2024) examined the implications of AI-enhanced ChatGPT submission in education. Abbas et al. (2023) explored the role of AI tools in enhancing students' educational performance at higher levels. Ali et al. (2024) examined the positive impact of AI on higher education, focusing on student learning experiences and academic integrity. Rouzegar and Makrehchi (2024) investigated the use of LLMs to develop tailored questions for math education. HILMI (2024) explored student and teacher perceptions of using Nearpod, an AI-driven educational application. Englmeier and Contreras (2024) discussed the use of AI in self-paced learning to foster sustainable knowledge acquisition. Li et al. (2024) explored how AI can address challenges in the education industry, such as teacher burnout and lack of personalized learning. Zohuri (2024) discussed the transformative impact of AI on personalized learning. Fenu et al. (2024) explored student interactions with AI support in C programming education. GOLUB et al. (2024) explored the role of AI in foreign language study. Singh and Pathania (2024) investigated the use of AI for content creation in digital marketing education. Magnago et al. (2024) examined the integration of AI and educational technologies into pedagogical practices. Alexsius

Pardosi et al. (2024) developed and implemented an AI-based learning management system for personalized learning. - and - (2024) compared and contrasted traditional schooling with AI-based learning. Vered et al. (2019) researched the use of AI agents to personalize medical conversations between patients and healthcare providers. State and Xatamova (2024) explored the application of AI in English for Specific Purposes (ESP) for law students. - et al. (2024) analyzed the role of AI in developing adaptive learning systems for personalized education. Shofiyyah et al. (2024) explored the transformation of Islamic religious education learning methods through the use of AI. Rahardjo et al. (2024) discussed the role of AI in creating smart campuses for personalized learning experiences. BUȘU (2024) examined the impact of AI on transforming traditional teaching methods. Yunusaliyev et al. (2024) described the developing paradigm of AI-driven learning environments and their effects on higher education. Khan and Veerendra (2024) explored the potential of AI in enhancing language acquisition and developing communication skills. Parsakia (2023) examined the impact of chatbots and AI on psychological aspects and cognitive skills in educational settings. Silva et al. (2024) explored the impact of AI on personalized learning and educational analytics. Bartholomew and Charles (2024) investigated the integration of AI and machine learning in STEM education. Samara et al. (2023) assessed graduate students' academic experiences with online education. Professor and Bhopal (2024) explored the opportunities and challenges of using AI in education. Namjoo et al. (2023) explored students' experiences with AI-assisted self-study. Pratama et al. (2023) explored how AI is revolutionizing education by personalizing learning. Baba et al. (2024) evaluated the impact of an AI-driven personalized mobile learning platform on student academic achievement. Madaminov and Urinov (2024) explored the contribution of AI to increasing students' achievements. Rekha et al. (2024) discussed the use of AI in personalized learning environments, focusing on student engagement and performance. Raj and Sathiyan (2024) explored the use of AI-driven recommendation systems for enhancing lifelong learning and mental health. Hanson and Yu (2024) explored how master's students perceive and experience using LLMs and AI-assisted software. Assistant Professor et al. (2024) explored the potential of AI in revolutionizing online education. Mohamed et al. (2025) investigated the possibilities of AI in personalized learning in Morocco. Phummapooti et al. (2024) explored the use of machine learning to predict students' suitability for digital majors based on their learning styles. Eder et al. (2021) presented a process for designing gamified learning experiences. Nur Fitria (2023) described the teacher's role in using AI for teaching and learning. Qadir (2023) discussed the use of generative AI, such as ChatGPT, in engineering education. Jelić and Tartalja (2023) highlighted the role of AI in improving communication in healthcare. Yu (2024) explored the challenges of adaptive learning within AI and proposed solutions. Nguyen (2024) investigated the use of NLP for teaching and learning Chinese. Ellikkal and Rajamohan (2024) explored the integration of self-determination theory principles into AI-driven personalized learning for management education. Tripon (2021) analyzed the need for holistic education and the use of video tools for personalized learning. Aggarwal et al. (2023) discussed the adoption of AI for the development of smart education. Anon (2023) investigated the impact of AI-driven personalized learning paths on educational outcomes. Lecturer et al. (2023) explored the transformative potential of AI in personalized learning. Chu et al. (2024) discussed the use of AI in Mobility-as-a-Service and its cybersecurity challenges. Wang et al. (2024) investigated how AI misrepresentations in personalized recommendations impact people's perceptions of AI. Humburg et al. (2024) highlighted middle schoolers' discussions on AI in learning, emphasizing the importance of student voices in AI design. Zaharuddin and Yao (2024) explored the impact of AI-driven personalized learning systems on student engagement. Bashiri and Kowsari (2024) analyzed the impact of LLMs and AI tools on student experiences on social media using UniversityCube data. Zhang (2020) examined few-shot reinforcement learning for personalized policy recommendations. Nash (2024) introduced the Decentralized Health Intelligence Network for personalized healthcare data management. Li and Yin (2024) investigated how AI recommendations and explanations influence human decision-making. Gbemisola and Olawale (2024) discussed AI and ML in HR practices for personalized employee experiences.

This comprehensive review showcases the multitude of ways AI is being used to personalize the learning experience, offering insights for researchers seeking to further explore and enhance the potential of AI in education. It emphasizes the need for continued research in addressing the ethical considerations, practical challenges, and accessibility issues related to AI integration, while highlighting its transformative potential in creating a more individualized and effective learning environment for all students.

References:

1. D., T., Do et al., 2024. PAIGE: Examining Learning Outcomes and Experiences with Personalized AI-Generated Educational Podcasts. arXiv. Available at: http://arxiv.org/abs/2409.04645v2.
2. Mollick, E. & Mollick, L., 2024. Instructors as Innovators: A future-focused approach to new AI learning opportunities, with prompts. arXiv. Available at: http://arxiv.org/abs/2407.05181v1.
3. Liu, Q., 2020. Modeling Dyadic Conversations for Personality Inference. arXiv. Available at: http://arxiv.org/abs/2009.12496v1.

4. Ramon, Y. et al., 2021. Explainable AI for Psychological Profiling from Digital Footprints: A Case Study of Big Five Personality Predictions from Spending Data. arXiv. Available at: http://arxiv.org/abs/2111.06908v1.
5. Daskalaki, E., Psaroudaki, K. & Fragopoulou, P., 2024. Navigating the Future of Education: Educators' Insights on AI Integration and Challenges in Greece, Hungary, Latvia, Ireland and Armenia. arXiv. Available at: http://arxiv.org/abs/2408.15686v1.
6. Jadeja, M. & Varia, N., 2017. Perspectives for Evaluating Conversational AI. arXiv. Available at: http://arxiv.org/abs/1709.04734v1.
7. Shih, V. et al., 2017. Towards personalized human AI interaction - adapting the behavior of AI agents using neural signatures of subjective interest. arXiv. Available at: http://arxiv.org/abs/1709.04574v1.
8. Kutt, K. et al., 2020. The BIRAFFE2 Experiment. Study in Bio-Reactions and Faces for Emotion-based Personalization for AI Systems. arXiv. Available at: http://arxiv.org/abs/2007.15048v2.
9. Yu, K., Guzdial, M. & Sturtevant, N., 2024. Evaluating the Effects of AI Directors for Quest Selection. arXiv. Available at: http://arxiv.org/abs/2410.03733v1.
10. Baillifard, A. et al., 2023. Implementing Learning Principles with a Personal AI Tutor: A Case Study. arXiv. Available at: http://arxiv.org/abs/2309.13060v1.
11. Cao, X. et al., 2022. PerFED-GAN: Personalized Federated Learning via Generative Adversarial Networks. arXiv. Available at: http://arxiv.org/abs/2202.09155v1.
12. Shi, Z. et al., 2024. Build Your Own Robot Friend: An Open-Source Learning Module for Accessible and Engaging AI Education. arXiv. Available at: http://arxiv.org/abs/2402.01647v1.
13. Chan, C. & Tsi, L., 2023. The AI Revolution in Education: Will AI Replace or Assist Teachers in Higher Education?. arXiv. Available at: http://arxiv.org/abs/2305.01185v1.
14. Kim, J. & Kim, K., 2024. The Hall of Singularity: VR Experience of Prophecy by AI. arXiv. Available at: http://arxiv.org/abs/2404.00033v1.
15. Kim, T. et al., 2024. Steering AI-Driven Personalization of Scientific Text for General Audiences. arXiv. Available at: http://arxiv.org/abs/2411.09969v1.
16. Cha, S., Ainooson, J. & Kunda, M., 2018. Quantifying Human Behavior on the Block Design Test Through Automated Multi-Level Analysis of Overhead Video. arXiv. Available at: http://arxiv.org/abs/1811.07488v1.
17. Vered, M., Dignum, F. & Miller, T., 2019. Let's Make It Personal, A Challenge in Personalizing Medical Inter-Human Communication. arXiv. Available at: http://arxiv.org/abs/1907.12687v1.
18. Ai, Q. et al., 2019. A Zero Attention Model for Personalized Product Search. arXiv. Available at: http://arxiv.org/abs/1908.11322v1.
19. Lyu, Y. et al., 2024. Designing AI-Enabled Games to Support Social-Emotional Learning for Children with Autism Spectrum Disorders. arXiv. Available at: http://arxiv.org/abs/2404.15576v1.

20. Alkaeed, ., Qayyum, A. & Qadir, J., 2023. Privacy Preservation in Artificial Intelligence and Extended Reality (AI-XR) Metaverses: A Survey. arXiv. Available at: http://arxiv.org/abs/2310.10665v1.
21. Ahmad, M. & Haddad, J., 2024. An Explainable AI Model for Predicting the Recurrence of Differentiated Thyroid Cancer. arXiv. Available at: http://arxiv.org/abs/2410.10907v1.
22. Kuo, M. et al., 2024. Enhancing Deep Knowledge Tracing via Diffusion Models for Personalized Adaptive Learning. arXiv. Available at: http://arxiv.org/abs/2405.05134v1.
23. Khamoushi, E., 2024. AI in Food Marketing from Personalized Recommendations to Predictive Analytics: Comparing Traditional Advertising Techniques with AI-Driven Strategies. arXiv. Available at: http://arxiv.org/abs/2410.01815v1.
24. Richardson, C. et al., 2023. Integrating Summarization and Retrieval for Enhanced Personalization via Large Language Models. arXiv. Available at: http://arxiv.org/abs/2310.20081v1.
25. Hao, R., Liu, D. & Hu, L., 2023. Enhancing Human Capabilities through Symbiotic Artificial Intelligence with Shared Sensory Experiences. arXiv. Available at: http://arxiv.org/abs/2305.19278v1.
26. Poretschkin, M. et al., 2023. Guideline for Trustworthy Artificial Intelligence -- AI Assessment Catalog. arXiv. Available at: http://arxiv.org/abs/2307.03681v1.
27. Kuhl, N., Lobana, J. & Meske, C., 2020. Do you comply with AI? -- Personalized explanations of learning algorithms and their impact on employees' compliance behavior. arXiv. Available at: http://arxiv.org/abs/2002.08777v1.
28. Hrnjic, E. & Tomczak, N., 2019. Machine learning and behavioral economics for personalized choice architecture. arXiv. Available at: http://arxiv.org/abs/1907.02100v1.
29. Takamido, R. et al., 2024. Understanding whole-body inter-personal dynamics between two players using neural Granger causality as the explainable AI (XAI). arXiv. Available at: http://arxiv.org/abs/2401.06412v1.
30. Wang, Q. et al., 2024. Navigating AI Fallibility: Examining People's Reactions and Perceptions of AI after Encountering Personality Misrepresentations. arXiv. Available at: http://arxiv.org/abs/2405.16355v1.
31. Ghafghazi, S. et al., 2021. AI-Augmented Behavior Analysis for Children with Developmental Disabilities: Building Towards Precision Treatment. arXiv. Available at: http://arxiv.org/abs/2102.10635v2.
32. Taheri, A. et al., 2024. Virtual Buddy: Redefining Conversational AI Interactions for Individuals with Hand Motor Disabilities. arXiv. Available at: http://arxiv.org/abs/2411.08228v1.
33. Zeng, Y. et al., 2022. Human Decision Makings on Curriculum Reinforcement Learning with Difficulty Adjustment. arXiv. Available at: http://arxiv.org/abs/2208.02932v1.

34. Riedl, C. & Bogert, E., 2024. Effects of AI Feedback on Learning, the Skill Gap, and Intellectual Diversity. arXiv. Available at: http://arxiv.org/abs/2409.18660v1.
35. Heo, G., Seo, J. & Whang, S., 2023. Personalized DP-SGD using Sampling Mechanisms. arXiv. Available at: http://arxiv.org/abs/2305.15165v1.
36. Bhatt, U. et al., 2023. Learning Personalized Decision Support Policies. arXiv. Available at: http://arxiv.org/abs/2304.06701v2.
37. Omelianenko, I., 2017. Applying Deep Machine Learning for psycho-demographic profiling of Internet users using O.C.E.A.N. model of personality. arXiv. Available at: http://arxiv.org/abs/1703.06914v2.
38. Zhang, M., 2020. Characterizing Policy Divergence for Personalized Meta-Reinforcement Learning. arXiv. Available at: http://arxiv.org/abs/2010.04816v1.
39. Nash, A., 2024. Decentralized Health Intelligence Network (DHIN). arXiv. Available at: http://arxiv.org/abs/2408.06240v4.
40. Li, Z. & Yin, M., 2024. Utilizing Human Behavior Modeling to Manipulate Explanations in AI-Assisted Decision Making: The Good, the Bad, and the Scary. arXiv. Available at: http://arxiv.org/abs/2411.10461v1.
41. Ramakrishnan, R. et al., 2023. Application of AI in Nutrition. arXiv. Available at: http://arxiv.org/abs/2312.11569v1.
42. Chu, K.-F. et al., 2024. A Survey of AI-Related Cyber Security Risks and Countermeasures in Mobility-as-a-Service. arXiv. Available at: http://arxiv.org/abs/2411.05681v1.
43. Sajja, R. et al., 2023. Artificial Intelligence-Enabled Intelligent Assistant for Personalized and Adaptive Learning in Higher Education. arXiv. Available at: http://arxiv.org/abs/2309.10892v1.
44. Xiong, Z. et al., 2024. A Review of Data Mining in Personalized Education: Current Trends and Future Prospects. arXiv. Available at: http://arxiv.org/abs/2402.17236v1.
45. Bashiri, M. & Kowsari, K., 2024. Transformative Influence of LLM and AI Tools in Student Social Media Engagement: Analyzing Personalization, Communication Efficiency, and Collaborative Learning. arXiv. Available at: http://arxiv.org/abs/2407.15012v1.
46. Wynn, A., Sucholutsky, I. & Griffiths, T., 2023. Learning Human-like Representations to Enable Learning Human Values. arXiv. Available at: http://arxiv.org/abs/2312.14106v3.
47. Morla, R., 2019. Ten AI Stepping Stones for Cybersecurity. arXiv. Available at: http://arxiv.org/abs/1912.06817v1.
48. Yan, Z., Xiang, Y. & Huang, Y., 2024. Social Life Simulation for Non-Cognitive Skills Learning. arXiv. Available at: http://arxiv.org/abs/2405.00273v2.
49. Rismani, S., Dobbe, R. & Moon, A., 2024. From Silos to Systems: Process-Oriented Hazard Analysis for AI Systems. arXiv. Available at: http://arxiv.org/abs/2410.22526v1.

50. Cui, W., Xue, Z. & Thai, K.-P., 2019. Performance comparison of an AI-based Adaptive Learning System in China. arXiv. Available at: http://arxiv.org/abs/1901.10268v1.
51. Akavova, A., Temirkhanova, Z. & Lorsanova, Z., 2023. Adaptive learning and artificial intelligence in the educational space M. Y. Tsoy, ed.. E3S Web of Conferences, 451, p.06011. Available at: https://doi.org/10.1051/e3sconf/202345106011.
52. Chima Abimbola Eden, Onyebuchi Nneamaka Chisom & Idowu Sulaimon Adeniyi, 2024. Integrating AI in education: Opportunities, challenges, and ethical considerations. Magna Scientia Advanced Research and Reviews, 10(2), pp.006–013. Available at: https://doi.org/10.30574/msarr.2024.10.2.0039.
53. Chima Abimbola Eden, Olabisi Oluwakemi Adeleye & Idowu Sulaimon Adeniyi, 2024. A review of AI-driven pedagogical strategies for equitable access to science education. Magna Scientia Advanced Research and Reviews, 10(2), pp.044–054. Available at: https://doi.org/10.30574/msarr.2024.10.2.0043.
54. Luo, Y., 2024. Revolutionizing education with AI: The adaptive cognitive enhancement model (ACEM) for personalized cognitive development. Applied and Computational Engineering, 82(1), pp.71–76. Available at: https://doi.org/10.54254/2755-2721/82/20240929.
55. Junior, J.C.G. et al., 2024. Inteligência Artificial e neuroeducação: O futuro do ensino personalizado. Lumen Et Virtus, 15(39), pp.2241–2251. Available at: https://doi.org/10.56238/levv15n39-051.
56. Oseremi Onesi-Ozigagun et al., 2024. Revolutionizing Education Through Ai: A Comprehensive Review Of Enhancing Learning Experiences. International Journal of Applied Research in Social Sciences, 6(4), pp.589–607. Available at: https://doi.org/10.51594/ijarss.v6i4.1011.
57. Hasibuan, R. & Andina Azizah, 2023. Analyzing the Potential of Artificial Intelligence (AI) in Personalizing Learning to Foster Creativity in Students. Enigma in Education, 1(1), pp.6–10. Available at: https://doi.org/10.61996/edu.v1i1.2.
58. Altaleb, H., Mouti, S. & Beegom, S., 2023. Enhancing College Education: An AI-driven Adaptive Learning Platform (ALP) for Customized Course Experiences. 2023 9th International Conference on Optimization and Applications (ICOA), 98, pp.1–5. Available at: https://doi.org/10.1109/ICOA58279.2023.10308834.
59. Yang, K.B. et al., 2023. Pair-Up: Prototyping Human-AI Co-orchestration of Dynamic Transitions between Individual and Collaborative Learning in the Classroom. Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems, pp.1–17. Available at: https://doi.org/10.1145/3544548.3581398.
60. Wang, T. et al., 2023. Exploring the Potential Impact of Artificial Intelligence (AI) on International Students in Higher Education: Generative AI, Chatbots, Analytics, and International Student Success. Applied Sciences, 13(11), p.6716. Available at: https://doi.org/10.3390/app13116716.

61. Do, T.D. et al., 2024. PAIGE: Examining Learning Outcomes and Experiences with Personalized AI-Generated Educational Podcasts. Available at: https://doi.org/10.48550/arXiv.2409.04645.
62. González, L.A. et al., 2022. Improving learning experiences in software engineering capstone courses using artificial intelligence virtual assistants. Computer Applications in Engineering Education, 30(5), pp.1370–1389. Available at: https://doi.org/10.1002/cae.22526.
63. Sajadi, S. et al., 2023. WIP: Using Generative AI to Assist in Individual Performance Feedback for Engineering Student Teams. 2023 IEEE Frontiers in Education Conference (FIE), pp.1–5. Available at: https://doi.org/10.1109/FIE58773.2023.10343517.
64. Moybeka, A.M.S. et al., 2023. Artificial Intelligence and English Classroom: The Implications of AI Toward EFL Students' Motivation. Edumaspul: Jurnal Pendidikan, 7(2), pp.2444–2454. Available at: https://doi.org/10.33487/edumaspul.v7i2.6669.
65. Chinenye Gbemisola Okatta, Funmilayo Aribidesi Ajayi & Olufunke Olawale, 2024. Navigating The Future: Integrating Ai And Machine Learning In Hr Practices For A Digital Workforce. Computer Science & IT Research Journal, 5(4), pp.1008–1030. Available at: https://doi.org/10.51594/csitrj.v5i4.1085.
66. RIZVI, M., 2023. Investigating AI-Powered Tutoring Systems that Adapt to Individual Student Needs, Providing Personalized Guidance and Assessments. The Eurasia Proceedings of Educational and Social Sciences, 31, pp.67–73. Available at: https://doi.org/10.55549/epess.1381518.
67. Niu, S.J. et al., 2022. Teachers' and Students' Views of Using an AI-Aided Educational Platform for Supporting Teaching and Learning at Chinese Schools. Education Sciences, 12(12), p.858. Available at: https://doi.org/10.3390/educsci12120858.
68. Baltezarević, R. & Baltezarević, I., 2024. Students' Attitudes on The Role of Artificial Intelligence (Ai) In Personalized Learning. International Journal of Cognitive Research in Science, Engineering and Education (IJCRSEE), 12(2), pp.387–397. Available at: https://doi.org/10.23947/2334-8496-2024-12-2-387-397.
69. Kretzschmar, V. et al., 2024. Enhanced Educational Experiences through Personalized and AI-based Learning. International Journal on Studies in Education, 6(2), pp.191–209. Available at: https://doi.org/10.46328/ijonse.206.
70. Shete, S.G., Koshti, P. & Pujari, V.I., 2024. The Impact of AI-Powered Personalization on Academic Performance in Students. 2024 5th International Conference on Recent Trends in Computer Science and Technology (ICRTCST), pp.295–301. Available at: https://doi.org/10.1109/ICRTCST61793.2024.10578480.
71. Abu Khurma, O. et al., 2024. AI ChatGPT and student engagement: Unraveling dimensions through PRISMA analysis for enhanced learning experiences.

Contemporary Educational Technology, 16(2), p.ep503. Available at: https://doi.org/10.30935/cedtech/14334.
72. Mutambik, I., 2024. The Use of AI-Driven Automation to Enhance Student Learning Experiences in the KSA: An Alternative Pathway to Sustainable Education. Sustainability, 16(14), p.5970. Available at: https://doi.org/10.3390/su16145970.
73. Strielkowski, W. et al., 2024. <scp>AI</scp>-driven adaptive learning for sustainable educational transformation. Sustainable Development. Available at: https://doi.org/10.1002/sd.3221.
74. Mollick, E.R. & Mollick, L., 2024. Instructors as Innovators: a Future-focused Approach to New AI Learning Opportunities, With Prompts. SSRN Electronic Journal. Available at: https://doi.org/10.2139/ssrn.4802463.
75. Anon, 2024. The Impact of AI-Powered Personalized Learning on Student Performance in Udaipur Colleges. Recent trends in Management and Commerce, 5(3), pp.86–93. Available at: https://doi.org/10.46632/rmc/5/3/14.
76. Olanike Abiola Ajuwon, Enitan Shukurat Animashaun & Njideka Rita Chiekezie, 2024. Innovative teaching strategies in mathematics and economics education: Engaging students through technology, AI, and Effective Mentoring. Open Access Research Journal of Science and Technology, 11(2), pp.128–137. Available at: https://doi.org/10.53022/oarjst.2024.11.2.0103.
77. Tashkent State Law University & Xatamova, N., 2024. The Future Of Legal English Learning: Integrating Ai Into Esp Education. Modern approaches and new trends in teaching foreign languages, pp.266–271. Available at: https://doi.org/10.52773/tsuull.conf.teach.foreign.lang.2024.8.5/pnxs6025.
78. -, M.N.Y., -, L.P.H. & -, S.N., 2024. Revolutionizing Education: Harnessing AI for Personalized Learning Pathways and Student Success. International Journal For Multidisciplinary Research, 6(5). Available at: https://doi.org/10.36948/ijfmr.2024.v06i05.28371.
79. Shofiyyah, N.A., Lesmana, O. & Tohari, H., 2024. Metamorphosis of Islamic Religious Education Learning Method: Classic Approach Converted by Artificial Intelligence (AI). Jurnal Pendidikan : Riset dan Konseptual, 8(2), p.265. Available at: https://doi.org/10.28926/riset_konseptual.v8i2.998.
80. Rahardjo, S. et al., 2024. Smart System with Leveraging AI Integrating System for well Designed Learning System. 2024 4th International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), pp.901–906. Available at: https://doi.org/10.1109/ICACITE60783.2024.10617214.
81. BUȘU, A.-F., 2024. AI-Powered Classrooms: A Revolution in Learning Environments. Analele Universității Din Craiova Seria Științe Filologice Limbi Străine Aplicate, 2024(1), pp.96–103. Available at: https://doi.org/10.52744/aucsflsa.2024.01.11.

82. Yunusaliyev, M., Yuldashev, I. & Yusupov, A., 2024. Revolutionizing the Present Education System Through AI-Driven Learning Platform with Hybrid Techniques. 2024 4th International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), pp.523–527. Available at: https://doi.org/10.1109/ICACITE60783.2024.10616605.
83. Anjum Khan & Dr. Veerendra Mishra, 2024. Adapting to Diversity: Leveraging AI for ESL Learning Enhancement. Journal of Advances and Scholarly Researches in Allied Education, 21(3), pp.188–198. Available at: https://doi.org/10.29070/kbp95r65.
84. Parsakia, K., 2023. The Effect of Chatbots and AI on The Self-Efficacy, Self-Esteem, Problem-Solving and Critical Thinking of Students. Health Nexus, 1(1), pp.71–76. Available at: https://doi.org/10.61838/hn.1.1.14.
85. Silva, G., Godwin, G. & Jayanagara, O., 2024. The Impact of AI on Personalized Learning and Educational Analytics. International Transactions on Education Technology (ITEE), 3(1), pp.36–46. Available at: https://doi.org/10.33050/itee.v3i1.669.
86. Olatunbosun Bartholomew Joseph & Nwankwo Charles Uzondu, 2024. Integrating AI and Machine Learning in STEM education: Challenges and opportunities. Computer Science & IT Research Journal, 5(8), pp.1732–1750. Available at: https://doi.org/10.51594/csitrj.v5i8.1379.
87. Samara, M. et al., 2023. How did online learning impact the academic performance of graduate students amid the Covid-19 pandemic?: A case study of the United Arab Emirates. Journal of Technology and Science Education, 13(3), p.869. Available at: https://doi.org/10.3926/jotse.2057.
88. Assistant Professor, Yadav, D.S. & The Bhopal School of Social Sciences College, Bhopal, 2024. Navigating The Landscape Of Ai Integration In Education: Opportunities, Challenges, And Ethical Considerations For Harnessing The Potential Of Artificial Intelligence (Ai) For Teaching And Learning. BSSS Journal of Computer, 15(1), pp.38–48. Available at: https://doi.org/10.51767/jc1503.
89. Namjoo, F. et al., 2023. Students Experience on Self-Study through AI. AI and Tech in Behavioral and Social Sciences, 1(3), pp.35–42. Available at: https://doi.org/10.61838/kman.aitech.1.3.6.
90. Pratama, M.P., Sampelolo, R. & Lura, H., 2023. Revolutionizing Education: Harnessing The Power Of Artificial Intelligence For Personalized Learning. Klasikal : Journal Of Education, Language Teaching And Science, 5(2), pp.350–357. Available at: https://doi.org/10.52208/klasikal.v5i2.877.
91. Baillifard, A. et al., 2023. Implementing Learning Principles with a Personal AI Tutor: A Case Study. Available at: https://doi.org/10.48550/arXiv.2309.13060.
92. Shu, X. & Gu, X., 2023. An Empirical Study of A Smart Education Model Enabled by the Edu-Metaverse to Enhance Better Learning Outcomes for Students. Systems, 11(2), p.75. Available at: https://doi.org/10.3390/systems11020075.

93. Konyrova, L., 2024. The Evolution of Language Learning: Exploring AI's Impact on Teaching English as a Second Language. Eurasian Science Review An International peer-reviewed multidisciplinary journal, 2(2), pp.133–138. Available at: https://doi.org/10.63034/esr-42.
94. Kenneth Holman et al., 2024. Navigating AI-Powered Personalized Learning in Special Education: A Guide for Preservice Teacher Faculty. Journal of Special Education Preparation, 4(2), pp.90–95. Available at: https://doi.org/10.33043/5b2xqcb3.
95. Wu, D. et al., 2024. Unlocking Potential: Key Factors Shaping Undergraduate Self-Directed Learning in AI-Enhanced Educational Environments. Systems, 12(9), p.332. Available at: https://doi.org/10.3390/systems12090332.
96. Hajeer, A., Papp-Váry, Á. & Pólya, É., 2024. AI Tutors vs. Human Instructors: Perceptions of Higher Education Students in Hungary and Spain. Edutec, Revista Electrónica de Tecnología Educativa, (89), pp.105–120. Available at: https://doi.org/10.21556/edutec.2024.89.3523.
97. Anon, 2024. AI-Driven Personalization in Higher Education: Enhancing Learning Outcomes through Adaptive Technologies. Adult and Higher Education, 6(6). Available at: https://doi.org/10.23977/aduhe.2024.060607.
98. Inoferio, H.V. et al., 2024. Coping with math anxiety and lack of confidence through AI-assisted Learning. Environment and Social Psychology, 9(5). Available at: https://doi.org/10.54517/esp.v9i5.2228.
99. Humburg, M. et al., 2024. Integrating Youth Perspectives into the Design of AI-Supported Collaborative Learning Environments. Education Sciences, 14(11), p.1197. Available at: https://doi.org/10.3390/educsci14111197.
100. Zaharuddin, Chen Yu & Yao, G., 2024. Enhancing Student Engagement with AI-Driven Personalized Learning Systems. International Transactions on Education Technology (ITEE), 3(1), pp.1–8. Available at: https://doi.org/10.33050/itee.v3i1.662.
101. Baba, K., El Faddouli, N.-E. & Cheimanoff, N., 2024. Mobile-Optimized AI-Driven Personalized Learning: A Case Study at Mohammed VI Polytechnic University. International Journal of Interactive Mobile Technologies (iJIM), 18(04), pp.81–96. Available at: https://doi.org/10.3991/ijim.v18i04.46547.
102. Madaminov, N. & Urinov, M., 2024. The Capacity of AI in Education System Towards in Acquiring the Innovative tested Models to Enhance the Learning Experience. 2024 4th International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), pp.556–560. Available at: https://doi.org/10.1109/ICACITE60783.2024.10616926.
103. Rekha, K. et al., 2024. Ai-Powered Personalized Learning System Design: Student Engagement And Performance Tracking System. 2024 4th International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), pp.1125–1130. Available at: https://doi.org/10.1109/ICACITE60783.2024.10617155.

104. Raj, J.D. & Sathiyan, G., 2024. Enhancing Life Skill Progression and Psychological Well-being of Undergraduate Students through AI-driven Recommendation System. Multidisciplinary Science Journal, 7(2), p.2025054. Available at: https://doi.org/10.31893/multiscience.2025054.
105. Hanson, J. & Yu, C.H. (Alex) ., 2024. Using AI-Enabled Tools to Support Minority Students' Success in HE. International Journal of Learning and Development, 14(3), p.59. Available at: https://doi.org/10.5296/ijld.v14i3.22263.
106. Assistant Professor, Department of Computer Science and Engineering, Roorkee Institute of Technology, Roorkee,(Haridwar) Uttarakhand, India. et al., 2024. Leveraging AI to Transform Online Higher Education: Focusing on Personalized Learning, Assessment, and Student Engagement. International Journal of Management and Humanities, 11(1), pp.1–6. Available at: https://doi.org/10.35940/ijmh.a1753.11010924.
107. Kolluru, V., Mungara, S. & Chintakunta, A.N., 2018. Adaptive Learning Systems: Harnessing AI for Customized Educational Experiences. International Journal of Computational Science and Information Technology, 6(3), pp.13–26. Available at: https://doi.org/10.5121/ijcsity.2018.6302.
108. Mohamed, K. et al., 2025. AI in Moroccan education: evaluating student acceptance using machine learning classification models. Indonesian Journal of Electrical Engineering and Computer Science, 37(1), p.452. Available at: https://doi.org/10.11591/ijeecs.v37.i1.pp452-462.
109. Phummapooti, R., Thanyaphongphat, J. & Panjaburee, P., 2024. AI-Driven Recommendations for Digital Majors Based on Learning Styles. 2024 5th Technology Innovation Management and Engineering Science International Conference (TIMES-iCON), pp.1–5. Available at: https://doi.org/10.1109/TIMES-iCON61890.2024.10630767.
110. Eder, G.-M.J. et al., 2021. Design of Gamified Learning Experiences. 2021 4th International Conference on Inclusive Technology and Education (CONTIE), pp.18–22. Available at: https://doi.org/10.1109/CONTIE54684.2021.00012.
111. Nur Fitria, T., 2023. The Use Of Artificial Intelligence In Education (Aied): Can Ai Replace The Teacher'S Role?. EPIGRAM (e-journal), 20(2), pp.165–187. Available at: https://doi.org/10.32722/epi.v20i2.5711.
112. Qadir, J., 2023. Engineering Education in the Era of ChatGPT: Promise and Pitfalls of Generative AI for Education. 2023 IEEE Global Engineering Education Conference (EDUCON), pp.1–9. Available at: https://doi.org/10.1109/EDUCON54358.2023.10125121.
113. Jelić, G. & Mamula Tartalja, D., 2023. How Can AI-Powered Solutions Improve Communication in Healthcare?. Seventh International Scientific Conference ITEMA Recent Advances in Information Technology, Tourism, Economics, Management and Agriculture, pp.81–88. Available at: https://doi.org/10.31410/itema.s.p.2023.81.

114. Yu, C., 2024. Research on Challenges and Strategies of Students' Adaptive Learning within AI. Journal of Education, Humanities and Social Sciences, 38, pp.117–124. Available at: https://doi.org/10.54097/mhkpyq51.
115. Nguyen, A.Q., 2024. Identifying Opportunities and Challenges in the Application of Natural Language Processing in Teaching and Learning Chinese for University Students: The Case of Viettel AI Platform in Vietnam. International Journal of Teaching, Learning and Education, 3(3), pp.1–8. Available at: https://doi.org/10.22161/ijtle.3.3.1.
116. Ellikkal, A. & Rajamohan, S., 2024. AI-enabled personalized learning: empowering management students for improving engagement and academic performance. Vilakshan - XIMB Journal of Management. Available at: https://doi.org/10.1108/xjm-02-2024-0023.
117. Tripon, C., 2021. Using Video-Tools To Maximize Classroom Time And Learning Experiences. eLearning and Software for Education, 2, pp.502–507. Available at: https://doi.org/10.12753/2066-026X-21-130.
118. Nazaretsky, T. et al., 2022. Empowering Teachers with AI: Co-Designing a Learning Analytics Tool for Personalized Instruction in the Science Classroom. LAK22: 12th International Learning Analytics and Knowledge Conference, pp.1–12. Available at: https://doi.org/10.1145/3506860.3506861.
119. Aggarwal, D., Sharma, D. & Saxena, A.B., 2023. Adoption of Artificial Intelligence (AI) For Development of Smart Education as the Future of a Sustainable Education System. Journal of Artificial Intelligence, Machine Learning and Neural Network, (36), pp.23–28. Available at: https://doi.org/10.55529/jaimlnn.36.23.28.
120. Anon, 2023. Personalized Learning Paths: Adapting Education with AI-Driven Curriculum. European Economic Letters. Available at: https://doi.org/10.52783/eel.v14i1.993.
121. Lecturer, Department of Computer Science Akshara First Grade College, Anekal et al., 2023. Leveraging Artificial Intelligence in Education: Transforming the Learning Landscape. International Research Journal of Computer Science, 10(05), pp.192–196. Available at: https://doi.org/10.26562/irjcs.2023.v1005.16.
122. Thuy An Ngo, T. et al., 2024. Unlocking Educational Potential: Exploring Students' Satisfaction and Sustainable Engagement with ChatGPT Using the ECM Model. Journal of Information Technology Education: Research, 23, p.021. Available at: https://doi.org/10.28945/5344.
123. Shaikh Zikra Riyaz & Shaikh Suvaid Salim, 2023. Google's Bard and Open AI's ChatGPT: Revolutionary AI Technologies and Their Impact on Education. International Journal of Advanced Research in Science, Communication and Technology, pp.195–202. Available at: https://doi.org/10.48175/ijarsct-12127.
124. Teresa, L.A. et al., 2023. Enhancing Children's Learning Experience: Interactive and Personalized Video Learning with AI Technology. 2023 IEEE International

Conference on Recent Advances in Systems Science and Engineering (RASSE), pp.1–5. Available at: https://doi.org/10.1109/RASSE60029.2023.10363506.
125. Kamruzzaman, M.M. et al., 2023. AI- and IoT-Assisted Sustainable Education Systems during Pandemics, such as COVID-19, for Smart Cities. Sustainability, 15(10), p.8354. Available at: https://doi.org/10.3390/su15108354.
126. Albdrani, R.N. & Al-Shargabi, A.A., 2023. Investigating the Effectiveness of ChatGPT for Providing Personalized Learning Experience: A Case Study. International Journal of Advanced Computer Science and Applications, 14(11). Available at: https://doi.org/10.14569/ijacsa.2023.01411122.
127. Mohammad Mazedul Huq Talukdar, E. al ., 2023. Impact of Artificial Intelligence based Learning Process on Students' Tendency to Involve in Independent Research at the Higher Secondary School. International Journal on Recent and Innovation Trends in Computing and Communication, 11(9), pp.4378–4384. Available at: https://doi.org/10.17762/ijritcc.v11i9.9924.
128. Кузьмин, Н.Н. et al., 2024. Artificial intelligence and its role in building an individual development trajectory for university students. Management of Education, 14(3-1(78)), pp.113–121. Available at: https://doi.org/10.25726/f3942-2092-6900-m.
129. Rodríguez Cairo, D. & Ramírez Echavarría, Y., 2023. Smart Tutors: improving the quality of higher education through AI. LatIA, 1, p.8. Available at: https://doi.org/10.62486/latia20238.
130. Rane, N., 2024. Enhancing the quality of teaching and learning through ChatGPT and similar large language models: Challenges, future prospects, and ethical considerations in education. TESOL and Technology Studies, 5(1), pp.1–6. Available at: https://doi.org/10.48185/tts.v5i1.1000.
131. Abbas, N. et al., 2023. Role of Artificial Intelligence Tools in Enhancing Students' Educational Performance at Higher Levels. Journal of Artificial Intelligence, Machine Learning and Neural Network, (35), pp.36–49. Available at: https://doi.org/10.55529/jaimlnn.35.36.49.
132. Ali, W. et al., 2024. Consensus or Controversy: Examining AI's Impact on Academic Integrity, Student Learning, and Inclusivity Within Higher Education Environments. 2024 2nd International Conference on Cyber Resilience (ICCR), pp.01–05. Available at: https://doi.org/10.1109/ICCR61006.2024.10532968.
133. Rouzegar, H. & Makrehchi, M., 2024. Generative AI for Enhancing Active Learning in Education: A Comparative Study of GPT-3.5 and GPT-4 in Crafting Customized Test Questions. arXiv. Available at: https://doi.org/10.48550/arXiv.2406.13903.
134. HILMI, C., 2024. The Students' And Teachers' Impression Toward Nearpod Apps In Learning English Of Curriculum Merdeka Perspectives. LEARNING : Jurnal Inovasi Penelitian Pendidikan dan Pembelajaran, 4(4), pp.1007–1016. Available at: https://doi.org/10.51878/learning.v4i4.3453.

135. Englmeier, K. & Contreras, P., 2024. How AI can Help Learners to Develop Conceptual Knowledge in Digital Learning Environments. 2024 IEEE 12th International Conference on Intelligent Systems (IS), pp.1–6. Available at: https://doi.org/10.1109/IS61756.2024.10705253.
136. Li, Y. et al., 2024. Revolutionizing Education through AI: Alleviating Educator Stress, Personalizing Learning, and Enhancing Economic Sustainability. World Journal of Education and Humanities, 6(5), p.p113. Available at: https://doi.org/10.22158/wjeh.v6n5p113.
137. Zohuri, B., 2024. Revolutionizing Education: The Dynamic Synergy of Personalized Learning and Artificial Intelligence. International Journal of Advanced Engineering and Management Research, 09(01), pp.143–153. Available at: https://doi.org/10.51505/ijaemr.2024.9111.
138. Fenu, G. et al., 2024. Exploring Student Interactions with AI in Programming Training. Adjunct Proceedings of the 32nd ACM Conference on User Modeling, Adaptation and Personalization, pp.555–560. Available at: https://doi.org/10.1145/3631700.3665227.
139. GOLUB, T.P. et al., 2024. Ai-Powered Pedagogy: Foreign Language Study In Higher Education. Академічні Студії. Серія «Педагогіка», (4), pp.50–56. Available at: https://doi.org/10.52726/as.pedagogy/2023.4.7.
140. Singh, B. & Pathania, D.A.K., 2024. AI-Driven Content Creation and Curation in Digital Marketing Education: Tools and Techniques. International Journal of Engineering Science and Humanities, 14(Special Issue 1), pp.14–26. Available at: https://doi.org/10.62904/8fbh3144.
141. Magnago, W. et al., 2024. Education 4.0: The Role Of Technology And Artificial Intelligence In The Future Of Learning. I Congresso Internacional Multidisciplinar (I CIM). Available at: https://doi.org/10.56238/i-cim-006.
142. Alexsius Pardosi, V.B. et al., 2024. Implementation of an Artificial Intelligence Based Learning Management System for Adaptive Learning. al-fikrah: Jurnal Manajemen Pendidikan, 12(1), p.149. Available at: https://doi.org/10.31958/jaf.v12i1.12548.
143. -, S.R. & -, S., 2024. Exploring the AI Era: A Comparative Analysis of AI-Driven Education and Traditional Teaching Methods. International Journal For Multidisciplinary Research, 6(4). Available at: https://doi.org/10.36948/ijfmr.2024.v06i04.24635.

1b: How can AI personalize learning experiences for individual students?

Execution time: 68.10

This question is at the forefront of educational research, as the potential of AI to tailor learning to individual needs is immense. This literature review examines recent research exploring various facets of AI-driven personalized learning, from content adaptation and delivery to implicit feedback mechanisms and ethical considerations.

One promising avenue for personalization lies in transforming existing educational materials into more engaging formats. D. et al. (2024) investigated the effectiveness of AI-generated podcasts, personalized to students' majors, interests, and learning styles, as an alternative to traditional textbooks. Their findings suggest that personalized podcasts significantly improved learning outcomes in certain subjects, highlighting the potential of AI to enhance content relevance and engagement. Complementing this approach, Mollick and Mollick (2024) explored how instructors can leverage generative AI to create personalized learning exercises, including simulations, mentoring, and co-creation activities. This instructor-driven approach empowers educators to design AI-powered experiences tailored to their students' specific needs, democratizing the development of educational technology.

Personalization requires understanding individual learner characteristics. Liu (2020) proposed a novel method for inferring personality from dyadic conversations, arguing that conversational dynamics offer richer insights than traditional methods relying on user-generated content. This approach could inform the design of AI systems that adapt to individual communication styles and preferences. Further, Ramon et al. (2021) demonstrated how Explainable AI (XAI) can be used to understand and validate models that predict psychological traits from digital footprints. This work emphasizes the importance of transparency in AI-driven personalization, allowing both educators and students to understand the basis for personalized recommendations.

The practical implementation of AI in education requires careful consideration of teacher perspectives and student engagement. Daskalaki et al. (2024) conducted a cross-national study exploring teachers' views on AI in education. Their findings reveal a cautious optimism, with teachers acknowledging the potential of AI for personalized learning while expressing concerns about critical thinking and ethical implications.

Jadeja and Varia (2017) focused on the evaluation of conversational AI systems, highlighting the importance of personalization in achieving user satisfaction and outlining the challenges in developing ideal conversational AI assistants.

Beyond explicit learner profiles, implicit feedback can further refine personalized learning. Shih et al. (2017) demonstrated how a hybrid brain-computer interface can provide implicit reinforcement to an AI agent, adapting its behavior to individual preferences. This approach opens up possibilities for AI systems that dynamically adjust to learners' subconscious reactions and engagement levels. Similarly, Kutt et al. (2020) explored the use of affective computing to capture emotional responses during gameplay, emphasizing the importance of personalized emotion models for natural human-AI interaction. This research suggests that incorporating affective data can enhance the personalization of learning experiences by adapting to individual emotional states.

Adapting game elements to individual preferences is another area of exploration. Yu et al. (2024) investigated the effectiveness of AI Directors in personalizing quest selection in video games, demonstrating that non-random AI Directors can enhance player experience. This research highlights the potential of AI to tailor challenges and activities to individual preferences, increasing engagement and motivation. Baillifard et al. (2023) explored the use of AI tutors to implement personalized retrieval practice and spaced repetition, finding that students who actively engaged with the AI tutor achieved significantly higher grades. This study demonstrates the practical application of AI in enhancing learning outcomes through personalized learning strategies.

Finally, addressing the technical challenges of personalized learning at scale is crucial. Cao et al. (2022) proposed a federated learning method that allows clients to design their own models without sharing sensitive data, enabling personalized model architectures while preserving privacy. Shi et al. (2024) developed an open-source learning module for building robot companions, providing students with hands-on experience in AI and emphasizing human-centered AI principles. This work promotes accessible and engaging AI education, allowing students to personalize their learning experience based on individual goals.

In conclusion, the research reviewed here demonstrates the multifaceted potential of AI to personalize learning experiences. From adapting content and delivery methods to incorporating implicit feedback and addressing ethical considerations, AI offers a range of tools and techniques to tailor learning to individual needs. Further research is needed to explore the long-term impact of these approaches and to ensure equitable access to the benefits of AI-powered personalized learning.

How can AI personalize learning experiences for individual students?

The integration of artificial intelligence (AI) in education holds immense potential for personalizing learning experiences, catering to individual student needs and fostering enhanced learning outcomes. Several research studies have explored various facets of this potential, offering valuable insights into the mechanisms and implications of AI-driven personalized learning.

One key aspect of personalization lies in adapting educational content and learning strategies to individual cognitive needs. Luo (2024) introduces the Adaptive Cognitive Enhancement Model (ACEM), an AI-driven framework that leverages machine learning algorithms and quantitative analysis to personalize cognitive development. ACEM encompasses cognitive profiling, adaptive learning paths, intelligent feedback, motivational strategies, and longitudinal tracking, demonstrating significant improvements in learning outcomes compared to traditional models. The model addresses challenges such as data privacy and scalability, highlighting the importance of responsible AI implementation in education. Similarly, Akavova et al. (2023) discuss the integration of adaptive learning technologies with AI algorithms to personalize learning experiences. By analyzing vast amounts of student data, AI can tailor content delivery and provide targeted interventions, improving learning outcomes and student engagement.

AI can also address disparities in access to quality education, particularly in fields like science. Abimbola and Sulaimon (2024) examine AI-driven pedagogical strategies that promote equitable access to science education. AI technologies can personalize learning experiences, provide real-time feedback, and enhance engagement among students from diverse backgrounds. Personalized learning platforms can adapt to individual learning styles and pace, offering additional support to students facing learning challenges. AI-driven assessment tools provide educators with valuable insights into student performance, enabling targeted interventions and promoting inclusivity. Abimbola and Sulaimon (2024) also highlight the ethical considerations of AI implementation, emphasizing the importance of responsible and equitable use.

Beyond adapting content, AI can personalize the communication of complex information. Kim et al. (2024) present TranSlider, an AI-powered tool that generates personalized translations of scientific text based on individual user profiles. This tool allows users to control the degree of personalization, leveraging LLMs to generate relatable and contextual translations. The study highlights the positive impact of personalized translations on user understanding and reading experiences, suggesting the potential of AI in facilitating communication in collaborative contexts. Similarly, Vered et al. (2019) address the challenge of personalizing communication in medical contexts. They propose the development of Intelligent Agents (IAs) to assist medical service providers and patients in establishing more personalized dialogues, leading to better treatment adherence and trust building.

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Finally, the role of human teachers in the age of AI remains crucial. Chan and Tsi (2023) explore the potential of AI in higher education, emphasizing the unique qualities of human teachers that are irreplaceable. While AI can assist teachers, the study highlights the importance of human interaction, critical thinking, and social-emotional competencies. The authors propose a roadmap for integrating AI effectively, ensuring a balanced and impactful learning experience. Kim and Kim (2024) explore the potential of AI in creating personalized experiences, even within artistic contexts, demonstrating how AI can be used Artificial intelligence (AI) is rapidly transforming the educational landscape, offering the potential to personalize learning experiences and cater to individual student needs. This literature review explores how AI can achieve this personalization, drawing upon a range of recent research.

Several studies highlight the potential of AI to tailor educational content and methods to individual learners. Hasibuan and Azizah (2023) emphasize AI's ability to identify individual learning styles, interests, and skills, enabling personalized resource allocation and learning experiences that foster creativity. Similarly, da Silva et al. (2024) explore the use of AI in K-12 education, demonstrating its capacity to provide real-time feedback and adapt content and pedagogical strategies to individual student needs. Altaleb et al. (2023) propose an Adaptive Learning Platform (ALP) that uses AI algorithms to customize course content and learning paths based on student level and learning behaviors. This personalized approach, as highlighted by Oseremi Onesi-Ozigagun et al. (2024), improves student engagement and academic performance by delivering content at the student's own pace and level of understanding.

Beyond content personalization, AI can also facilitate dynamic learning experiences. Yang et al. (2023) investigate how technology can support teachers in orchestrating dynamic transitions between individual and collaborative learning activities, using intelligent tutoring systems. Their research reveals the potential tension between teacher and student preferences for control over these transitions, highlighting the need for careful design in human-AI co-orchestration within the classroom. Junior et al. (2024) explore the integration of AI with neuroeducation, suggesting that understanding brain function can further enhance the personalization of learning by tailoring teaching methods to cognitive capabilities and neural development.

The application of AI-driven personalization extends to specific student populations and learning modalities. Wang et al. (2023) examine the impact of AI on the education of international students, exploring applications such as personalized learning, adaptive testing, and chatbots. Do et al. (2024) investigate the effectiveness of AI-generated podcasts personalized to learner profiles, finding that this modality transformation of textbook material can significantly improve learning outcomes. González et al. (2022) propose using AI virtual assistants combined with recommender systems to leverage collective knowledge and enhance learning experiences in software engineering capstone courses.

Furthermore, AI can support instructors in providing personalized feedback and managing teamwork. Sajadi et al. (2023) present the use of generative AI to create individual performance summaries based on peer evaluations, offering a solution for providing confidential and formative feedback in large project-based learning courses. Moybeka et al. (2023) explore the impact of AI on EFL student motivation, highlighting how AI-driven learning environments can enhance intrinsic motivation and self-efficacy. Finally, Gbemisola and Olawale (2024) discuss the integration of AI in HR practices, emphasizing its potential to personalize employee experiences and improve decision-making processes, which can indirectly benefit student learning experiences through enhanced organizational efficiency and effectiveness.

In conclusion, these studies demonstrate the diverse ways in which AI can personalize learning experiences, from tailoring content and learning paths to facilitating dynamic transitions and providing personalized feedback. However, challenges remain, including ethical considerations, data privacy, and the need for teacher training and student control. Addressing these challenges is crucial for realizing the full potential of AI in creating truly personalized and effective learning experiences for all students.

Literature Review: How can AI personalize learning experiences for individual students? This question is at the forefront of educational research, as the potential of AI to tailor learning to individual needs is immense. This literature review examines recent research exploring various facets of AI-driven personalized learning, from content adaptation and delivery to implicit feedback mechanisms and ethical considerations.

One promising avenue for personalization lies in transforming existing educational materials into more engaging formats. D. et al. (2024) investigated the effectiveness of AI-generated podcasts, personalized to students' majors, interests, and learning styles, as an alternative to traditional textbooks. Their findings suggest that personalized podcasts significantly improved learning outcomes in certain subjects, highlighting the potential of AI to enhance content relevance and engagement. Complementing this approach, Mollick and Mollick (2024) explored how instructors can leverage generative AI to create personalized learning exercises, including simulations, mentoring, and co-creation activities. This instructor-driven approach empowers educators to design AI-powered experiences tailored to their students' specific needs, democratizing the development of educational technology.

Personalization requires understanding individual learner characteristics. Liu (2020) proposed a novel method for inferring personality from dyadic conversations, arguing that conversational dynamics offer richer insights than traditional methods relying on user-generated content. This approach could inform the design of AI systems that adapt to individual communication styles and preferences. Further, Ramon et al. (2021) demonstrated how Explainable AI (XAI) can be used to understand and validate models that predict psychological traits from digital footprints. This work emphasizes the importance of transparency in AI-driven personalization, allowing both educators and students to understand the basis for personalized recommendations.

The practical implementation of AI in education requires careful consideration of teacher perspectives and student engagement. Daskalaki et al. (2024) conducted a cross-national study exploring teachers' views on AI in education. Their findings reveal a cautious optimism, with teachers acknowledging the potential of AI for personalized learning while expressing concerns about critical thinking and ethical implications. Jadeja and Varia (2017) focused on the evaluation of conversational AI systems, highlighting the importance of personalization in achieving user satisfaction and outlining the challenges in developing ideal conversational AI assistants.

Beyond explicit learner profiles, implicit feedback can further refine personalized learning. Shih et al. (2017) demonstrated how a hybrid brain-computer interface can provide implicit reinforcement to an AI agent, adapting its behavior to individual preferences. This approach opens up possibilities for AI systems that dynamically adjust to learners' subconscious reactions and engagement levels. Similarly, Kutt et al. (2020) explored the use of affective computing to capture emotional responses during gameplay, emphasizing the importance of personalized emotion models for natural human-AI interaction. This research suggests that incorporating affective data can enhance the personalization of learning experiences by adapting to individual emotional states.

Adapting game elements to individual preferences is another area of exploration. Yu et al. (2024) investigated the effectiveness of AI Directors in personalizing quest selection in video games, demonstrating that non-random AI Directors can enhance player experience. This research highlights the potential of AI to tailor challenges and activities to individual preferences, increasing engagement and motivation. Baillifard et al. (2023) explored the use of AI tutors to implement personalized retrieval practice and spaced repetition, finding that students who actively engaged with the AI tutor achieved significantly higher grades. This study demonstrates the practical application of AI in enhancing learning outcomes through personalized learning strategies.

Finally, addressing the technical challenges of personalized learning at scale is crucial. Cao et al. (2022) proposed a federated learning method that allows clients to design their own models without sharing sensitive data, enabling personalized model architectures while preserving privacy. Shi et al. (2024) developed an open-source learning module for building robot companions, providing students with hands-on experience in AI and emphasizing human-centered AI principles. This work promotes accessible and engaging AI education, allowing students to personalize their learning experience based on individual goals.

In conclusion, the research reviewed here demonstrates the multifaceted potential of AI to personalize learning experiences. From adapting content and delivery methods to incorporating implicit feedback and addressing ethical considerations, AI offers a range of tools and techniques to tailor learning to individual needs. Further research is needed to explore the long-term impact of these approaches and to ensure equitable access to the benefits of AI-powered personalized learning.

How can AI personalize learning experiences for individual students?

The integration of artificial intelligence (AI) in education holds immense potential for personalizing learning experiences, catering to individual student needs and fostering enhanced learning outcomes. Several research studies have explored various facets of this potential, offering valuable insights into the mechanisms and implications of AI-driven personalized learning.

One key aspect of personalization lies in adapting educational content and learning strategies to individual cognitive needs. Luo (2024) introduces the Adaptive Cognitive Enhancement Model (ACEM), an AI-driven framework that leverages machine learning algorithms and quantitative analysis to personalize cognitive development. ACEM encompasses cognitive profiling, adaptive learning paths, intelligent feedback, motivational strategies, and longitudinal tracking, demonstrating significant improvements in learning outcomes compared to traditional models. The model addresses challenges such as data privacy and scalability, highlighting the importance of responsible AI implementation in education. Similarly, Akavova et al. (2023) discuss the integration of adaptive learning technologies with AI algorithms to personalize learning experiences. By analyzing vast amounts of student data, AI can tailor content delivery and provide targeted interventions, improving learning outcomes and student engagement.

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References:

1. D., T., Do et al., 2024. PAIGE: Examining Learning Outcomes and Experiences with Personalized AI-Generated Educational Podcasts. arXiv. Available at: http://arxiv.org/abs/2409.04645v2.
2. Mollick, E. & Mollick, L., 2024. Instructors as Innovators: A future-focused approach to new AI learning opportunities, with prompts. arXiv. Available at: http://arxiv.org/abs/2407.05181v1.
3. Liu, Q., 2020. Modeling Dyadic Conversations for Personality Inference. arXiv. Available at: http://arxiv.org/abs/2009.12496v1.
4. Ramon, Y. et al., 2021. Explainable AI for Psychological Profiling from Digital Footprints: A Case Study of Big Five Personality Predictions from Spending Data. arXiv. Available at: http://arxiv.org/abs/2111.06908v1.
5. Daskalaki, E., Psaroudaki, K. & Fragopoulou, P., 2024. Navigating the Future of Education: Educators' Insights on AI Integration and Challenges in Greece, Hungary, Latvia, Ireland and Armenia. arXiv. Available at: http://arxiv.org/abs/2408.15686v1.
6. Jadeja, M. & Varia, N., 2017. Perspectives for Evaluating Conversational AI. arXiv. Available at: http://arxiv.org/abs/1709.04734v1.
7. Shih, V. et al., 2017. Towards personalized human AI interaction - adapting the behavior of AI agents using neural signatures of subjective interest. arXiv. Available at: http://arxiv.org/abs/1709.04574v1.
8. Kutt, K. et al., 2020. The BIRAFFE2 Experiment. Study in Bio-Reactions and Faces for Emotion-based Personalization for AI Systems. arXiv. Available at: http://arxiv.org/abs/2007.15048v2.
9. Yu, K., Guzdial, M. & Sturtevant, N., 2024. Evaluating the Effects of AI Directors for Quest Selection. arXiv. Available at: http://arxiv.org/abs/2410.03733v1.
10. Baillifard, A. et al., 2023. Implementing Learning Principles with a Personal AI Tutor: A Case Study. arXiv. Available at: http://arxiv.org/abs/2309.13060v1.

11. Cao, X. et al., 2022. PerFED-GAN: Personalized Federated Learning via Generative Adversarial Networks. arXiv. Available at: http://arxiv.org/abs/2202.09155v1.
12. Shi, Z. et al., 2024. Build Your Own Robot Friend: An Open-Source Learning Module for Accessible and Engaging AI Education. arXiv. Available at: http://arxiv.org/abs/2402.01647v1.
13. Chan, C. & Tsi, L., 2023. The AI Revolution in Education: Will AI Replace or Assist Teachers in Higher Education?. arXiv. Available at: http://arxiv.org/abs/2305.01185v1.
14. Kim, J. & Kim, K., 2024. The Hall of Singularity: VR Experience of Prophecy by AI. arXiv. Available at: http://arxiv.org/abs/2404.00033v1.
15. Kim, T. et al., 2024. Steering AI-Driven Personalization of Scientific Text for General Audiences. arXiv. Available at: http://arxiv.org/abs/2411.09969v1.
16. Cha, S., Ainooson, J. & Kunda, M., 2018. Quantifying Human Behavior on the Block Design Test Through Automated Multi-Level Analysis of Overhead Video. arXiv. Available at: http://arxiv.org/abs/1811.07488v1.
17. Vered, M., Dignum, F. & Miller, T., 2019. Let's Make It Personal, A Challenge in Personalizing Medical Inter-Human Communication. arXiv. Available at: http://arxiv.org/abs/1907.12687v1.
18. Ai, Q. et al., 2019. A Zero Attention Model for Personalized Product Search. arXiv. Available at: http://arxiv.org/abs/1908.11322v1.
19. Lyu, Y. et al., 2024. Designing AI-Enabled Games to Support Social-Emotional Learning for Children with Autism Spectrum Disorders. arXiv. Available at: http://arxiv.org/abs/2404.15576v1.
20. Alkaeed, ., Qayyum, A. & Qadir, J., 2023. Privacy Preservation in Artificial Intelligence and Extended Reality (AI-XR) Metaverses: A Survey. arXiv. Available at: http://arxiv.org/abs/2310.10665v1.
21. Akavova, A., Temirkhanova, Z. & Lorsanova, Z., 2023. Adaptive learning and artificial intelligence in the educational space M. Y. Tsoy, ed.. E3S Web of Conferences, 451, p.06011. Available at: https://doi.org/10.1051/e3sconf/202345106011.
22. Chima Abimbola Eden, Onyebuchi Nneamaka Chisom & Idowu Sulaimon Adeniyi, 2024. Integrating AI in education: Opportunities, challenges, and ethical considerations. Magna Scientia Advanced Research and Reviews, 10(2), pp.006–013. Available at: https://doi.org/10.30574/msarr.2024.10.2.0039.
23. Chima Abimbola Eden, Olabisi Oluwakemi Adeleye & Idowu Sulaimon Adeniyi, 2024. A review of AI-driven pedagogical strategies for equitable access to science education. Magna Scientia Advanced Research and Reviews, 10(2), pp.044–054. Available at: https://doi.org/10.30574/msarr.2024.10.2.0043.
24. Luo, Y., 2024. Revolutionizing education with AI: The adaptive cognitive enhancement model (ACEM) for personalized cognitive development. Applied and Computational Engineering, 82(1), pp.71–76. Available at: https://doi.org/10.54254/2755-2721/82/20240929.

25. Junior, J.C.G. et al., 2024. Inteligência Artificial e neuroeducação: O futuro do ensino personalizado. Lumen Et Virtus, 15(39), pp.2241–2251. Available at: https://doi.org/10.56238/levv15n39-051.
26. da Silva, M.C.F. et al., 2024. The Integration Of Artificial Intelligence Into The Personalization Of Education: A New Paradigm For Basic Education. Aracê, 6(3). Available at: https://doi.org/10.56238/arev6n3-100.
27. Oseremi Onesi-Ozigagun et al., 2024. Revolutionizing Education Through Ai: A Comprehensive Review Of Enhancing Learning Experiences. International Journal of Applied Research in Social Sciences, 6(4), pp.589–607. Available at: https://doi.org/10.51594/ijarss.v6i4.1011.
28. Hasibuan, R. & Andina Azizah, 2023. Analyzing the Potential of Artificial Intelligence (AI) in Personalizing Learning to Foster Creativity in Students. Enigma in Education, 1(1), pp.6–10. Available at: https://doi.org/10.61996/edu.v1i1.2.
29. Altaleb, H., Mouti, S. & Beegom, S., 2023. Enhancing College Education: An AI-driven Adaptive Learning Platform (ALP) for Customized Course Experiences. 2023 9th International Conference on Optimization and Applications (ICOA), 98, pp.1–5. Available at: https://doi.org/10.1109/ICOA58279.2023.10308834.
30. Yang, K.B. et al., 2023. Pair-Up: Prototyping Human-AI Co-orchestration of Dynamic Transitions between Individual and Collaborative Learning in the Classroom. Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems, pp.1–17. Available at: https://doi.org/10.1145/3544548.3581398.
31. Wang, T. et al., 2023. Exploring the Potential Impact of Artificial Intelligence (AI) on International Students in Higher Education: Generative AI, Chatbots, Analytics, and International Student Success. Applied Sciences, 13(11), p.6716. Available at: https://doi.org/10.3390/app13116716.
32. Do, T.D. et al., 2024. PAIGE: Examining Learning Outcomes and Experiences with Personalized AI-Generated Educational Podcasts. Available at: https://doi.org/10.48550/arXiv.2409.04645.
33. González, L.A. et al., 2022. Improving learning experiences in software engineering capstone courses using artificial intelligence virtual assistants. Computer Applications in Engineering Education, 30(5), pp.1370–1389. Available at: https://doi.org/10.1002/cae.22526.
34. Sajadi, S. et al., 2023. WIP: Using Generative AI to Assist in Individual Performance Feedback for Engineering Student Teams. 2023 IEEE Frontiers in Education Conference (FIE), pp.1–5. Available at: https://doi.org/10.1109/FIE58773.2023.10343517.
35. Moybeka, A.M.S. et al., 2023. Artificial Intelligence and English Classroom: The Implications of AI Toward EFL Students' Motivation. Edumaspul: Jurnal Pendidikan, 7(2), pp.2444–2454. Available at: https://doi.org/10.33487/edumaspul.v7i2.6669.

36. Chinenye Gbemisola Okatta, Funmilayo Aribidesi Ajayi & Olufunke Olawale, 2024. Navigating The Future: Integrating Ai And Machine Learning In Hr Practices For A Digital Workforce. Computer Science & IT Research Journal, 5(4), pp.1008–1030. Available at: https://doi.org/10.51594/csitrj.v5i4.1085.

2a: How effectively can AI identify knowledge gaps in individual students and recommend tailored resources?

Execution time: 65.81

The effective identification of individual student knowledge gaps and subsequent recommendation of tailored resources by AI systems is a rapidly evolving field of research with significant implications for personalized learning. Several studies highlight the potential of AI in addressing this challenge using various approaches. Personalized adaptive learning (PAL) utilizes knowledge tracing, a crucial technique that models student knowledge evolution to predict future performance and offer personalized resource recommendations (Kuo et al., 2024). Specifically, Deep Knowledge Tracing (DKT), enhanced by deep learning, shows promise in accurately predicting student academic outcomes, particularly with models like SAKT and KQN, which allow for proactive interventions to support student progress (Kuo et al., 2024). Another approach leverages generative AI models like TabDDPM, a diffusion model, to generate synthetic educational records to augment training data for DKT, demonstrating improved performance, especially in scenarios with limited training data (Kuo et al., 2024). Similarly, LLMs can identify knowledge components within dialogue turns and diagnose student correctness, enabling knowledge tracing in tutor-student conversations, outperforming existing KT methods (Scarlatos and Lan, 2024).

Beyond knowledge tracing, researchers are exploring various strategies for personalization and recommendation. Generative AI can transform existing learning materials, such as converting textbook chapters into personalized podcasts tailored to individual learning styles and interests, resulting in improved learning outcomes and increased engagement (D. et al., 2024). The importance of tailoring learning experiences to individual competencies is emphasized by the Artemis system, which uses competency relation graphs to visualize student progress and generate personalized learning paths recommending relevant resources (Sölch et al., 2023). Furthermore, AI-Lab, a pedagogical framework, guides students in leveraging GenAI within programming courses by highlighting both benefits and risks, offering strategies for effective prompt engineering, and exploring student perceptions of GenAI (Dickey et al., 2023). These personalized approaches can also extend to recommending optimal course sequences that consider prerequisite requirements, course availability, and student contextual backgrounds to minimize time to graduation and maximize GPA (Xu et al., 2015).

However, effective implementation of AI in education faces challenges. Data sparsity can hinder knowledge concept recommendation in MOOCs, prompting the development of graph neural network-based approaches like ACKRec, which leverage content and context information to learn entity representations and personalize recommendations (Wang et al., 2020). Similarly, limitations in considering diverse learning materials when modeling student knowledge growth led to the development of multi-view knowledge models like MVKM, which capture knowledge growth from various resource types (Zhao et al., 2020). Addressing the limitations of traditional multiple-choice tests, AI-powered bots can analyze student explanations for their answers, identifying missing concepts and providing actionable feedback for instructors (Klymkowsky and Cooper, 2024). Even with advanced models, the capacity gap between large language models and conventional sequential models poses a challenge for knowledge distillation in recommender systems. DLLM2Rec tackles this challenge by filtering reliable knowledge and integrating collaborative signals (Cui et al., 2024).

Further research emphasizes the importance of addressing ethical considerations and practical implementation challenges. Concerns regarding algorithmic bias and unequal support for minority students necessitate responsible AI frameworks for Learning Analytics in Higher Education, prioritizing transparency, fairness, and accountability (Tirado et al., 2024). The need for explainability and trust in AI systems is addressed through Human-Centric eXplainable AI (HCXAI) frameworks, particularly in educational contexts using LLMs (Maity and Deroy, 2024). Practical implementation aspects include designing user-friendly interfaces like Rocket, a Tinder-like interface for Interactive Educational Systems, which enhances explainability, enables self-personalization, and allows students to track their learning progress (Choi et al., 2020). Integrating AI tutors with learning programs based on learning science principles, such as personalized retrieval practice and spaced repetition, has shown promising results in enhancing academic performance (Baillifard et al., 2023).

Furthermore, AI's role extends beyond personalized recommendations to facilitating knowledge sharing and management. Organizational barriers to effective knowledge management highlight the need for improving employee actions through training and guidelines (Koivisto and Taipalus, 2023). In the realm of knowledge tracing, a comprehensive review of existing methods, from early attempts to deep learning approaches, reveals research gaps and future directions (Abdelrahman et al., 2022). Knowledge Augmented Data Teaching (KADT) optimizes data teaching strategies by tracing student knowledge progress over multiple learning concepts, leading to improved performance across various machine learning tasks (Abdelrahman and Wang, 2021). The use of attention-based graph convolutional networks for student performance prediction considers the complex relationships between courses and student knowledge acquisition, offering accurate predictions and identifying at-risk students (Hu and Rangwala, 2019). AI is also being integrated into online educational forums, acting as an auxiliary More Knowledgeable Other (MKO) to reduce instructor workload and enhance the quality and speed of responses to student queries (Sinha et al., 2024).

Several studies also explore specific applications of AI in education. Research into children's misconceptions about AI reveals the need for pedagogically sound AI-literacy curricula (Mertala and Fagerlund, 2023). The proliferation of AI-generated image tools democratizes creative processes, but also raises concerns about image quality, cost, and copyright (Tang et al., 2024). Cognitive biases, such as anthropomorphism, can impact human-AI collaboration, emphasizing the need for tailored AI product design in hiring settings (Olszewski, 2024). AI diffusion across economies, especially in developing nations, raises questions about its labor market impact and the need for redistribution mechanisms (Lipcsey, 2024). Ethical considerations and principle-implementation gaps in AI highlight the importance of contextual evaluation and global collaboration (Tidjon and Khomh, 2022). In e-commerce, combining semantic web mining with BP neural networks allows for personalized page recommendations that better meet user needs (Badouch and Boutaounte, 2024). The User-Oriented Smart General AI System (UOGASuCI) leverages causal inference to identify optimal user characteristics and improve model performance by recommending updates to individualized tacit knowledge and technical preferences (Peng, 2021). Addressing FATE (fairness, accountability, transparency, and ethics) concerns in AI, particularly in the global South, requires community-led strategies for responsible AI design (Inuwa-Dutse, 2023). Human-AI collaboration in feature engineering harnesses the strengths of both humans and AI, but user perceptions and the semantic clarity of suggestions impact feature adoption (Zhu et al., 2024). Addressing policy gaps related to AI misuse in education, a novel AI framework for autonomous assessment and grading is proposed, emphasizing the need for increased awareness of AI tools among academics (Khan et al., 2024). Accessible AI education is promoted through the development of open-source learning modules, enabling students to build robot companions and gain hands-on experience in AI, robotics, and AI ethics (Shi et al., 2024). Hierarchical Topology Distillation (HTD) in Recommender Systems addresses the capacity gap between teacher and student models by transferring topological structure hierarchically (Kang et al., 2021). AI-driven strategies in food marketing offer personalization and efficiency, surpassing traditional methods in meeting consumer demands (Khamoushi, 2024). AI emergency preparedness requires frameworks to address potential national security threats related to AI, drawing from fields like counterterrorism and cybersecurity (Wasil et al., 2024). Finally, the impact of LLMs and AI tools on student engagement with social media is evident in enhanced academic performance, critical thinking skills, and collaborative opportunities (Bashiri and Kowsari, 2024). While a comprehensive review of research, access to validated research instruments, and effective communication between stakeholders are essential for informed decision-making in education, ongoing research is vital to optimize educational interventions and their effects on student outcomes (Fashola, 2004). Instructors can leverage generative AI to create personalized learning experiences through customized prompts and AI-based exercises that facilitate novel forms of practice and application such as simulations and coaching (Mollick and Mollick, 2024). Context-aware recommender systems for learning personalization can benefit from incorporating pedagogical foundations from learning theories to better align recommendations with educational goals and learner needs (Abu-Rasheed et al., 2023). Lastly, Human-AI systems like Tutor CoPilot have the potential to scale expertise in tutoring by providing real-time expert-like guidance to tutors, thereby improving student mastery, particularly for students working with less experienced tutors (Wang et al., 2024). Through continued exploration and development of these diverse approaches, AI can effectively address the challenge of identifying individual student knowledge gaps and recommending tailored resources to optimize learning outcomes.

References:

1. Kuo, M. et al., 2024. Enhancing Deep Knowledge Tracing via Diffusion Models for Personalized Adaptive Learning. arXiv. Available at: http://arxiv.org/abs/2405.05134v1.
2. D., T., Do et al., 2024. PAIGE: Examining Learning Outcomes and Experiences with Personalized AI-Generated Educational Podcasts. arXiv. Available at: http://arxiv.org/abs/2409.04645v2.
3. Xiong, Z. et al., 2024. A Review of Data Mining in Personalized Education: Current Trends and Future Prospects. arXiv. Available at: http://arxiv.org/abs/2402.17236v1.
4. Sölch, M., Aberle, M. & Krusche, S., 2023. Integrating Competency-Based Education in Interactive Learning Systems. arXiv. Available at: http://arxiv.org/abs/2309.12343v1.

5. Dickey, E., Bejarano, A. & Garg, C., 2023. Innovating Computer Programming Pedagogy: The AI-Lab Framework for Generative AI Adoption. arXiv. Available at: http://arxiv.org/abs/2308.12258v1.
6. Koivisto, K. & Taipalus, T., 2023. Pitfalls in Effective Knowledge Management: Insights from an International Information Technology Organization. arXiv. Available at: http://arxiv.org/abs/2304.07737v2.
7. Scarlatos, A. & Lan, A., 2024. Exploring Knowledge Tracing in Tutor-Student Dialogues. arXiv. Available at: http://arxiv.org/abs/2409.16490v1.
8. Hicke, Y., 2023. Knowledge Tracing Challenge: Optimal Activity Sequencing for Students. arXiv. Available at: http://arxiv.org/abs/2311.14707v1.
9. Khosravi, H., Cooper, K. & Kitto, K., 2017. RiPLE: Recommendation in Peer-Learning Environments Based on Knowledge Gaps and Interests. arXiv. Available at: http://arxiv.org/abs/1704.00556v1.
10. Borchers, C. et al., 2023. Revealing Networks: Understanding Effective Teacher Practices in AI-Supported Classrooms using Transmodal Ordered Network Analysis. arXiv. Available at: http://arxiv.org/abs/2312.10826v1.
11. Qi, L. et al., 2024. A Knowledge-Component-Based Methodology for Evaluating AI Assistants. arXiv. Available at: http://arxiv.org/abs/2406.05603v1.
12. Cui, Y. et al., 2024. Distillation Matters: Empowering Sequential Recommenders to Match the Performance of Large Language Model. arXiv. Available at: http://arxiv.org/abs/2405.00338v3.
13. Ali, S. et al., 2023. Constructing Dreams using Generative AI. arXiv. Available at: http://arxiv.org/abs/2305.12013v1.
14. Abdelrahman, G., Wang, Q. & Nunes, B., 2022. Knowledge Tracing: A Survey. arXiv. Available at: http://arxiv.org/abs/2201.06953v1.
15. Wang, S. et al., 2020. Attentional Graph Convolutional Networks for Knowledge Concept Recommendation in MOOCs in a Heterogeneous View. arXiv. Available at: http://arxiv.org/abs/2006.13257v1.
16. Zeng, Z. et al., 2023. Too Many Cooks: Exploring How Graphical Perception Studies Influence Visualization Recommendations in Draco. arXiv. Available at: http://arxiv.org/abs/2308.14241v1.
17. Zhao, S., Wang, C. & Sahebi, S., 2020. Modeling Knowledge Acquisition from Multiple Learning Resource Types. arXiv. Available at: http://arxiv.org/abs/2006.13390v2.
18. Klymkowsky, M. & Cooper, M., 2024. The end of multiple choice tests: using AI to enhance assessment. arXiv. Available at: http://arxiv.org/abs/2406.07481v1.
19. Xi, Y. et al., 2024. Efficient and Deployable Knowledge Infusion for Open-World Recommendations via Large Language Models. arXiv. Available at: http://arxiv.org/abs/2408.10520v1.

20. Tang, Y. et al., 2024. Exploring the Impact of AI-generated Image Tools on Professional and Non-professional Users in the Art and Design Fields. arXiv. Available at: http://arxiv.org/abs/2406.10640v1.
21. Olszewski, S., 2024. Designing Human-AI Systems: Anthropomorphism and Framing Bias on Human-AI Collaboration. arXiv. Available at: http://arxiv.org/abs/2404.00634v2.
22. Lipcsey, R., 2024. AI Diffusion to Low-Middle Income Countries; A Blessing or a Curse?. arXiv. Available at: http://arxiv.org/abs/2405.20399v2.
23. Tidjon, L. & Khomh, F., 2022. The Different Faces of AI Ethics Across the World: A Principle-Implementation Gap Analysis. arXiv. Available at: http://arxiv.org/abs/2206.03225v1.
24. Badouch, M. & Boutaounte, M., 2024. Smart E-commerce Recommendations with Semantic AI. arXiv. Available at: http://arxiv.org/abs/2409.01137v3.
25. Peng, H., 2021. User-Oriented Smart General AI System under Causal Inference. arXiv. Available at: http://arxiv.org/abs/2103.14561v2.
26. Xu, J., Xing, T. & van der Schaar, M., 2015. Personalized Course Sequence Recommendations. arXiv. Available at: http://arxiv.org/abs/1512.09176v2.
27. Inuwa-Dutse, I., 2023. FATE in AI: Towards Algorithmic Inclusivity and Accessibility. arXiv. Available at: http://arxiv.org/abs/2301.01590v2.
28. Zhu, Q. et al., 2024. Towards Feature Engineering with Human and AI's Knowledge: Understanding Data Science Practitioners' Perceptions in Human&AI-Assisted Feature Engineering Design. arXiv. Available at: http://arxiv.org/abs/2405.14107v1.
29. Khan, W. et al., 2024. Auto-assessment of assessment: A conceptual framework towards fulfilling the policy gaps in academic assessment practices. arXiv. Available at: http://arxiv.org/abs/2411.08892v1.
30. Shi, Z. et al., 2024. Build Your Own Robot Friend: An Open-Source Learning Module for Accessible and Engaging AI Education. arXiv. Available at: http://arxiv.org/abs/2402.01647v1.
31. Kang, S. et al., 2021. Topology Distillation for Recommender System. arXiv. Available at: http://arxiv.org/abs/2106.08700v1.
32. Khamoushi, E., 2024. AI in Food Marketing from Personalized Recommendations to Predictive Analytics: Comparing Traditional Advertising Techniques with AI-Driven Strategies. arXiv. Available at: http://arxiv.org/abs/2410.01815v1.
33. Wasil, A. et al., 2024. AI Emergency Preparedness: Examining the federal government's ability to detect and respond to AI-related national security threats. arXiv. Available at: http://arxiv.org/abs/2407.17347v2.
34. Bashiri, M. & Kowsari, K., 2024. Transformative Influence of LLM and AI Tools in Student Social Media Engagement: Analyzing Personalization, Communication Efficiency, and Collaborative Learning. arXiv. Available at: http://arxiv.org/abs/2407.15012v1.

35. Tirado, A., Mulholland, P. & Fernandez, M., 2024. Towards an Operational Responsible AI Framework for Learning Analytics in Higher Education. arXiv. Available at: http://arxiv.org/abs/2410.05827v1.
36. Zhao, Z. et al., 2023. Talking Models: Distill Pre-trained Knowledge to Downstream Models via Interactive Communication. arXiv. Available at: http://arxiv.org/abs/2310.03188v1.
37. Abdelrahman, G. & Wang, Q., 2021. Learning Data Teaching Strategies Via Knowledge Tracing. arXiv. Available at: http://arxiv.org/abs/2111.07083v1.
38. Hu, Q. & Rangwala, H., 2019. Academic Performance Estimation with Attention-based Graph Convolutional Networks. arXiv. Available at: http://arxiv.org/abs/2001.00632v1.
39. Sinha, A. et al., 2024. BoilerTAI: A Platform for Enhancing Instruction Using Generative AI in Educational Forums. arXiv. Available at: http://arxiv.org/abs/2409.13196v1.
40. Wijekoon, A. et al., 2024. iSee: Advancing Multi-Shot Explainable AI Using Case-based Recommendations. arXiv. Available at: http://arxiv.org/abs/2408.12941v1.
41. Okpala, E. et al., 2024. AI-Cybersecurity Education Through Designing AI-based Cyberharassment Detection Lab. arXiv. Available at: http://arxiv.org/abs/2405.08125v2.
42. Chung, K. et al., 2021. Masked Deep Q-Recommender for Effective Question Scheduling. arXiv. Available at: http://arxiv.org/abs/2112.10125v1.
43. Mertala, P. & Fagerlund, J., 2023. Finnish 5th and 6th graders' misconceptions about Artificial Intelligence. arXiv. Available at: http://arxiv.org/abs/2311.16644v1.
44. Kuo, M.-M. et al., 2024. Deep Knowledge Tracing for Personalized Adaptive Learning at Historically Black Colleges and Universities. arXiv. Available at: http://arxiv.org/abs/2410.13876v1.
45. Baillifard, A. et al., 2023. Implementing Learning Principles with a Personal AI Tutor: A Case Study. arXiv. Available at: http://arxiv.org/abs/2309.13060v1.
46. Abu-Rasheed, H., Weber, C. & Fathi, M., 2023. Context based learning: a survey of contextual indicators for personalized and adaptive learning recommendations. A pedagogical and technical perspective. arXiv. Available at: http://arxiv.org/abs/2308.16661v1.
47. Wang, R. et al., 2024. Tutor CoPilot: A Human-AI Approach for Scaling Real-Time Expertise. arXiv. Available at: http://arxiv.org/abs/2410.03017v1.
48. Maity, S. & Deroy, A., 2024. Human-Centric eXplainable AI in Education. arXiv. Available at: http://arxiv.org/abs/2410.19822v1.
49. Choi, Y. et al., 2020. Choose Your Own Question: Encouraging Self-Personalization in Learning Path Construction. arXiv. Available at: http://arxiv.org/abs/2005.03818v1.
50. Mollick, E. & Mollick, L., 2024. Instructors as Innovators: A future-focused approach to new AI learning opportunities, with prompts. arXiv. Available at: http://arxiv.org/abs/2407.05181v1.

51. Fashola, O.S., 2004. Being an Informed Consumer of Quantitative Educational Research. Phi Delta Kappan, 85(7), pp.532–538. Available at: https://doi.org/10.1177/003172170408500712.

2b: How effectively can AI identify knowledge gaps in individual students and recommend tailored resources?

Execution time: 12.70

The integration of artificial intelligence (AI) in education has garnered significant attention, particularly in its capacity to identify knowledge gaps in individual students and recommend tailored resources. This literature review synthesizes recent research findings that explore the effectiveness of AI in personalizing learning experiences, thereby addressing the research question: "How effectively can AI identify knowledge gaps in individual students and recommend tailored resources?"

Kuo et al. (2024) emphasize the role of personalized adaptive learning (PAL) in closely monitoring student progress and customizing learning paths to meet individual needs. A pivotal aspect of effective PAL is knowledge tracing, which involves modeling students' evolving knowledge to predict future performance. The authors highlight advancements in deep learning, particularly through Deep Knowledge Tracing (DKT), which has been enhanced by generative AI models. These models address data scarcity challenges by generating synthetic educational records, thereby augmenting training data for DKT. The study's findings demonstrate that the use of the TabDDPM diffusion model significantly improves DKT performance, particularly in scenarios with limited training data. This suggests that AI can effectively identify knowledge gaps by leveraging enhanced data generation techniques, ultimately leading to more personalized educational recommendations.

In a complementary study, D. et al. (2024) investigate the transformative potential of generative AI in content creation, specifically through the development of AI-generated podcasts derived from textbook chapters. The research involved a user study with 180 college students, comparing traditional textbook reading with both generalized and personalized AI-generated podcasts. The personalized podcasts were tailored to align with students' majors, interests, and learning styles. The results indicated that students preferred the AI-generated podcast format over traditional textbooks, with personalized versions leading to significantly improved learning outcomes, albeit with variations across subjects. This study underscores the importance of personalization in educational resources, suggesting that AI can not only identify knowledge gaps but also enhance engagement and effectiveness through tailored content delivery.

Together, these studies illustrate the potential of AI to revolutionize educational practices by identifying individual learning needs and providing customized resources. The advancements in knowledge tracing and content personalization highlight a promising direction for future research and application in educational technology. As AI continues to evolve, its ability to address knowledge gaps and recommend tailored resources will likely play a crucial role in fostering more effective and engaging learning experiences for students. The integration of artificial intelligence (AI) in educational settings has garnered significant attention for its potential to identify knowledge gaps in individual students and recommend tailored resources. This literature review synthesizes recent research findings that explore the effectiveness of AI in personalizing education, focusing on how these technologies can enhance learning outcomes by addressing individual student needs.

Xiong et al. (2024) provide a comprehensive overview of personalized education through the lens of educational technology and AI. Their research emphasizes the role of data mining techniques in optimizing the learning process by analyzing academic performance, learning preferences, and behaviors. By categorizing advancements in personalized educational data mining into four primary scenarios—educational recommendation, cognitive diagnosis, knowledge tracing, and learning analysis—the authors highlight how AI can effectively identify knowledge gaps. This structured taxonomy not only aids in understanding the current landscape but also points to future research directions that could further enhance the personalization of learning experiences.

In a complementary study, Sölch et al. (2023) focus on the Artemis interactive learning system, which aims to provide competency-based education tailored to individual student characteristics. The authors argue that traditional learning systems often fail to adapt content to the unique capabilities and experiences of students. By developing a competency relation graph, Artemis can measure and visualize a student's progress toward mastering specific competencies. This innovative approach allows the system to generate personalized learning paths that recommend relevant resources, thereby addressing knowledge gaps more effectively. The user study presented in their research indicates that the newly designed competency visualization significantly enhances usability, suggesting that such systems can be instrumental in fostering personalized learning environments.

Together, these studies underscore the transformative potential of AI in education. By leveraging data mining and competency-based frameworks, AI systems can not only identify where students struggle but also provide tailored recommendations that cater to their individual learning journeys. As educational technologies continue to evolve, the insights from Xiong et al. (2024) and Sölch et al. (2023) pave the way for future innovations aimed at creating more adaptive and responsive learning experiences. This literature review highlights the importance of ongoing research in this field, as the effective identification of knowledge gaps and the provision of personalized resources remain critical to enhancing educational outcomes for diverse student populations. The integration of Artificial Intelligence (AI) in educational settings has garnered significant attention, particularly regarding its potential to identify knowledge gaps in individual students and recommend tailored resources. This literature review synthesizes recent research findings to explore the effectiveness of AI in this context, addressing the research question: "How effectively can AI identify knowledge gaps in individual students and recommend tailored resources?"

Dickey et al. (2023) highlight the dual-edged nature of Generative AI (GenAI) in education, particularly among Computer Science students. Their research indicates that a substantial percentage of students (48.5%) utilize GenAI for homework, raising concerns about over-dependence on these tools. The authors propose the "AI-Lab" framework, which aims to guide students in leveraging GenAI effectively while preserving core skill development. This framework not only emphasizes the identification of GenAI's errors but also suggests its use for tailored support, such as providing detailed examples and debugging assistance. By fostering a balanced approach to GenAI usage, the AI-Lab framework seeks to enhance the learning experience and address individual knowledge gaps, thereby demonstrating the potential of AI to recommend resources that are aligned with students' specific needs.

In a complementary vein, Fashola (2004) underscores the importance of informed decision-making among educators regarding the adoption of educational programs and resources. The author argues that disparities in educational quality necessitate a tailored approach to addressing the unique challenges faced by different schools and districts. Fashola emphasizes that understanding the specific needs and contexts of students is crucial for selecting effective interventions. This perspective aligns with the notion that AI can serve as a powerful tool for identifying knowledge gaps, as it can analyze individual student performance data and recommend resources that are specifically designed to meet those needs. The challenge, however, lies in ensuring that the AI systems are equipped to understand the diverse contexts in which they operate, thereby enhancing their effectiveness in recommending tailored resources.

Together, these studies illustrate the potential of AI to not only identify knowledge gaps but also to facilitate the selection of appropriate educational resources. The AI-Lab framework proposed by Dickey et al. (2023) provides a structured approach for educators to harness the capabilities of GenAI, while Fashola (2004) emphasizes the necessity of contextual understanding in the implementation of educational interventions. As researchers continue to explore the intersection of AI and education, it is imperative to consider both the technological capabilities of AI systems and the nuanced realities of educational environments to maximize their effectiveness in supporting student learning.
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References:

1. Kuo, M. et al., 2024. Enhancing Deep Knowledge Tracing via Diffusion Models for Personalized Adaptive Learning. arXiv. Available at: http://arxiv.org/abs/2405.05134v1.
2. D., T., Do et al., 2024. PAIGE: Examining Learning Outcomes and Experiences with Personalized AI-Generated Educational Podcasts. arXiv. Available at: http://arxiv.org/abs/2409.04645v2.
3. Xiong, Z. et al., 2024. A Review of Data Mining in Personalized Education: Current Trends and Future Prospects. arXiv. Available at: http://arxiv.org/abs/2402.17236v1.
4. Sölch, M., Aberle, M. & Krusche, S., 2023. Integrating Competency-Based Education in Interactive Learning Systems. arXiv. Available at: http://arxiv.org/abs/2309.12343v1.
5. Dickey, E., Bejarano, A. & Garg, C., 2023. Innovating Computer Programming Pedagogy: The AI-Lab Framework for Generative AI Adoption. arXiv. Available at: http://arxiv.org/abs/2308.12258v1.
6. Fashola, O.S., 2004. Being an Informed Consumer of Quantitative Educational Research. Phi Delta Kappan, 85(7), pp.532–538. Available at: https://doi.org/10.1177/003172170408500712.

3a: Can AI-powered tools reduce the language barrier in multilingual classrooms and foster inclusivity?

Execution time: 82.20

This literature review examines the potential of AI-powered tools to mitigate language barriers and promote inclusivity in multilingual classrooms. Several studies highlight the promise of AI in facilitating cross-lingual communication and enhancing learning experiences for diverse student populations. For instance, research demonstrates that multilingual Large Language Models (LLMs) can be effectively applied to generate personalized feedback for teachers, encouraging growth mindset supportive language (GMSL) and potentially improving student learning outcomes (Handa et al., 2023). This suggests the potential of LLMs to bridge communication gaps and create a more inclusive classroom environment. Furthermore, approaches like vocabulary trimming can reduce the size of multilingual LMs, facilitating the development of language-specific models without extensive retraining, potentially benefiting low-resource languages and limiting harmful biases (Ushio et al., 2023).

Improving speech recognition in diverse classroom settings is another key area where AI can contribute. Continued pre-training of models like Wav2vec2.0 has proven effective in enhancing robustness to different noises, microphones, and classroom demographics, facilitating more accurate and inclusive speech recognition (Attia et al., 2024). Beyond the classroom, AI can also support self-regulated and collaborative language learning through mobile technologies, providing personalized learning paths and fostering essential learning skills (Viberg and Kukulska-Hulme, 2021). Within the classroom, LLMs can empower reciprocal questioning through flipped interaction techniques, enabling students to generate questions rather than simply receiving answers, promoting active learning, and allowing teachers to personalize training pathways (Tan, 2023).

Addressing the scarcity of multilingual image captions, the ICU framework leverages existing English image captioning models and multilingual language models to perform cross-lingual image understanding, demonstrating the potential of AI to overcome language barriers in multimodal learning (Wu, 2023). However, while LLMs exhibit promising surface-level cross-lingual abilities, challenges persist in deeper crosslingual knowledge transfer, necessitating explicit optimization strategies to unlock their full potential (Chua et al., 2024). AI also holds promise for supporting students with special needs. Studies have shown that social robots, such as the NAO robot, can enhance engagement and improve educational outcomes for students with Autism Spectrum Disorder (ASD) in classroom settings (Yang et al., 2024).

Tools like MRA, a web application that translates and annotates radiology text, exemplify the potential of AI to overcome language barriers in specialized domains, making information accessible to a wider audience (Campos and Couto, 2017). Furthermore, personalized chatbot-based teaching assistants powered by LLMs can provide tailored support to students, particularly in large classrooms or where direct teacher presence is limited (Kumar et al., 2023). However, it's important to acknowledge the potential biases in multilingual models. Research has shown that grammatical structures from higher-resource languages can influence lower-resource languages, highlighting the need for linguistically-aware fluency evaluation

(Papadimitriou et al., 2022). LLM tutors can be a valuable resource for non-native English speaking students, providing accessible and tailored support in computing education and overcoming language barriers (Molina et al., 2024).

AI-powered tools can also enhance traditional learning methodologies. Simulation robotics offers interactive learning experiences that go beyond traditional robotics classroom methods (Karagounis, 2023), while sign.mt demonstrates the potential of real-time multilingual translation between spoken and signed languages, promoting inclusive communication for the deaf community (Moryossef, 2023). Addressing the challenge of negative interference in multilingual models, neuron specialization, a method that modularizes feed-forward layers based on language-specific neuron activation, shows promise in improving performance and promoting knowledge transfer in multilingual translation (Tan et al., 2024). Ensuring the truthfulness of multilingual LLMs is another important consideration, and approaches like Fact-aware Multilingual Selective Synergy (FaMSS) aim to enhance factual accuracy across languages (Liu et al., 2024).

AI can also support classroom dialogue analysis. A comprehensive rule base of dialogue sequences combined with an LLM-powered AI agent can accurately categorize classroom interactions, providing valuable insights for improving teaching practices (Long and Zhang, 2024). Addressing the performance limitations of multilingual models compared to monolingual ones, Cross-lingual Expert Language Models (X-ELM) offer a modular approach that specializes language models on subsets of the multilingual corpus, improving performance and facilitating extensibility to new languages (Blevins et al., 2024). AI can also support the objective quantification of behaviors in students with ASD in real-world classroom environments, providing valuable data for tracking intervention effectiveness (Das et al., 2024).

Mitigating toxicity in multilingual LLMs is crucial, and zero-shot cross-lingual generalization of preference tuning has proven effective in reducing toxic outputs across various languages (Li et al., 2024). Leveraging existing multilingual linguistic resources, such as thesauri and gazetteers, can simplify the development of multilingual and cross-lingual language technology applications (Steinberger et al., 2006). Adapting medical LLMs to local languages can improve access to healthcare services, and novel MoE routing methods can enhance multilingual generalization while preserving interpretability (Zheng et al., 2024). Addressing fairness in multilingual multimodal models, research has introduced notions of multilingual individual and group fairness, highlighting biases in performance and error distribution across languages (Wang et al., 2021).

AI can enhance flipped classroom approaches by providing tools that capture student perceptions and address challenges in online learning environments, particularly for non-mathematics students enrolled in statistics courses (Kristanto and Padmi, 2020). NL2VIS tools like Chat2VIS demonstrate the potential of LLMs to generate data visualizations from multilingual natural language requests, making data analysis more accessible (Maddigan and Susnjak, 2023). AI can also predict specificity in classroom discussions, providing insights into discussion quality and pedagogical effectiveness (Lugini and Litman, 2019). Automating the generation of multilingual talking avatar videos with tools like Virbo can significantly reduce production costs and facilitate video-based learning and marketing (Zhang et al., 2024).

Large datasets of classroom transcripts, combined with NLP models, can analyze dialogic discourse moves and their correlation with learning outcomes, providing valuable information for improving K-12 instruction (Demszky and Hill, 2022). AI can also be used to analyze and destigmatize language related to substance use disorders on social media platforms like Reddit, fostering more supportive online environments (Bouzoubaa et al., 2024). Addressing the challenges of managing large, multilingual codebases, research has proposed a rigorous design approach and the MLSA architecture for lightweight static analysis of multilingual software (Lyons et al., 2019). Developing powerful multilingual math reasoning LLMs, like MathOctopus, shows promise in improving math reasoning capabilities across various languages (Chen et al., 2023).

AI can also address accessibility challenges in education. The Classroom Slide Narration System (CSNS) generates audio descriptions of slide content, making presentations accessible to blind and visually impaired students (V. et al., 2022). Leveraging the relatedness of languages within the same family through multilingual fine-tuning can improve performance on downstream NLP tasks, particularly for low-resource languages (Dhamecha et al., 2021). Simplifying the development of multilingual NLP applications, the Europe Media Monitor demonstrates the feasibility of processing and analyzing large volumes of online news articles in multiple languages (Steinberger, 2014). SimClass, a multi-agent classroom simulation framework, demonstrates the potential of LLMs to simulate classroom interactions and enhance user learning experiences (Zhang et al., 2024).

Investigating the impact of machine translation as a continued training objective, research has shown that explicit sentence-level alignment can be detrimental to cross-lingual transfer pretraining (Ji et al., 2024). Tools like EIT, the Earnest Insight Toolkit, can assess student engagement in interactive lecture participation exercises, providing valuable information for educators to identify at-risk students (Miroyan et al., 2023). Qtok, a tool for assessing tokenizer quality in multilingual contexts, highlights the importance of tokenization in multilingual LLM development (Chelombitko et al., 2024). The MLSA architecture facilitates the analysis of large, multilingual codebases, addressing challenges in managing inter-language calls and code complexity (Lyons et al., 2018).

Addressing multilingualism in ontologies, research has identified various modeling approaches and highlighted the need for better tooling support in ontology editors (Gillis-Webber and Keet, 2022). Tools like OpusCleaner and OpusTrainer simplify the development of high-quality machine translation systems and large language models, lowering the entry barrier for newcomers to the field (Bogoychev et al., 2023). Research on multilingual speech-to-speech translation has demonstrated the feasibility of supporting multiple target languages, enabling spoken communication across various language pairs (Gong et al., 2023). Studying the adaptation of multilingual models to low-resource settings, research has investigated the interaction of vocabulary augmentation and script transliteration, highlighting the potential of these approaches (Chau and Smith, 2021).

Finally, research has investigated the effects of multilinguality on language modeling performance, showing that adding multilingual data can improve performance in low-resource languages but may negatively impact high-resource languages (Chang et al., 2023). Addressing bias in multilingual text classification, a debiasing framework based on contrastive learning has been proposed, offering a more general debiasing method and a comprehensive evaluation framework (Lin et al., 2023). And a multi-task recurrent model incorporating language recognition can improve performance in multilingual speech recognition systems (Tang et al., 2016). Furthermore, research has shown that multilingual instruction tuning of LLMs can significantly improve instruction-following capabilities across various languages, including those not seen during tuning (Shaham et al., 2024). Finally, studies on multilingual SLU have explored cross-lingual knowledge transfer and proposed novel model architectures to improve performance (Do et al., 2020). Challenging the paradigm of pre-translation in multilingual applications, research has shown that direct inference with models like PaLM2 can lead to better performance in many languages (Intrator et al., 2024).

References:

1. Handa, K. et al., 2023. "Mistakes Help Us Grow": Facilitating and Evaluating Growth Mindset Supportive Language in Classrooms. arXiv. Available at: http://arxiv.org/abs/2310.10637v1.

2. Ushio, A., Zhou, Y. & Camacho-Collados, J., 2023. An Efficient Multilingual Language Model Compression through Vocabulary Trimming. arXiv. Available at: http://arxiv.org/abs/2305.15020v3.
3. Attia, A. et al., 2024. CPT-Boosted Wav2vec2.0: Towards Noise Robust Speech Recognition for Classroom Environments. arXiv. Available at: http://arxiv.org/abs/2409.14494v1.
4. Viberg, O. & Kukulska-Hulme, A., 2021. Fostering learners' self-regulation and collaboration skills and strategies for mobile language learning beyond the classroom. arXiv. Available at: http://arxiv.org/abs/2104.12486v1.
5. Tan, C., 2023. Large Language Model-Driven Classroom Flipping: Empowering Student-Centric Peer Questioning with Flipped Interaction. arXiv. Available at: http://arxiv.org/abs/2311.14708v1.
6. Wu, G., 2023. ICU: Conquering Language Barriers in Vision-and-Language Modeling by Dividing the Tasks into Image Captioning and Language Understanding. arXiv. Available at: http://arxiv.org/abs/2310.12531v3.
7. Chua, L. et al., 2024. Crosslingual Capabilities and Knowledge Barriers in Multilingual Large Language Models. arXiv. Available at: http://arxiv.org/abs/2406.16135v1.
8. Yang, Q. et al., 2024. Surprising Performances of Students with Autism in Classroom with NAO Robot. arXiv. Available at: http://arxiv.org/abs/2407.12014v1.
9. Campos, L. & Couto, F., 2017. MRA - Proof of Concept of a Multilingual Report Annotator Web Application. arXiv. Available at: http://arxiv.org/abs/1704.01748v3.
10. Attia, A. et al., 2024. Continued Pretraining for Domain Adaptation of Wav2vec2.0 in Automatic Speech Recognition for Elementary Math Classroom Settings. arXiv. Available at: http://arxiv.org/abs/2405.13018v1.
11. Kumar, H. et al., 2023. Impact of Guidance and Interaction Strategies for LLM Use on Learner Performance and Perception. arXiv. Available at: http://arxiv.org/abs/2310.13712v3.
12. Papadimitriou, I., Lopez, K. & Jurafsky, D., 2022. Multilingual BERT has an accent: Evaluating English influences on fluency in multilingual models. arXiv. Available at: http://arxiv.org/abs/2210.05619v2.
13. Molina, I. et al., 2024. Leveraging LLM Tutoring Systems for Non-Native English Speakers in Introductory CS Courses. arXiv. Available at: http://arxiv.org/abs/2411.02725v1.
14. Karagounis, A., 2023. Robotics as a Simulation Educational Tool. arXiv. Available at: http://arxiv.org/abs/2312.05582v1.
15. Moryossef, A., 2023. sign.mt: Real-Time Multilingual Sign Language Translation Application. arXiv. Available at: http://arxiv.org/abs/2310.05064v2.
16. Tan, S., Wu, D. & Monz, C., 2024. Neuron Specialization: Leveraging intrinsic task modularity for multilingual machine translation. arXiv. Available at: http://arxiv.org/abs/2404.11201v1.

17. Liu, W. et al., 2024. Towards Truthful Multilingual Large Language Models: Benchmarking and Alignment Strategies. arXiv. Available at: http://arxiv.org/abs/2406.14434v1.
18. Long, Y. & Zhang, Y., 2024. Enhanced Classroom Dialogue Sequences Analysis with a Hybrid AI Agent: Merging Expert Rule-Base with Large Language Models. arXiv. Available at: http://arxiv.org/abs/2411.08418v1.
19. Blevins, T. et al., 2024. Breaking the Curse of Multilinguality with Cross-lingual Expert Language Models. arXiv. Available at: http://arxiv.org/abs/2401.10440v2.
20. Das, B. et al., 2024. Explainable Artificial Intelligence for Quantifying Interfering and High-Risk Behaviors in Autism Spectrum Disorder in a Real-World Classroom Environment Using Privacy-Preserving Video Analysis. arXiv. Available at: http://arxiv.org/abs/2407.21691v1.
21. Li, X., Yong, Z.-X. & Bach, S., 2024. Preference Tuning For Toxicity Mitigation Generalizes Across Languages. arXiv. Available at: http://arxiv.org/abs/2406.16235v2.
22. Steinberger, R., Pouliquen, B. & Ignat, C., 2006. Exploiting multilingual nomenclatures and language-independent text features as an interlingua for cross-lingual text analysis applications. arXiv. Available at: http://arxiv.org/abs/cs/0609064v1.
23. Zheng, G. et al., 2024. Efficiently Democratizing Medical LLMs for 50 Languages via a Mixture of Language Family Experts. arXiv. Available at: http://arxiv.org/abs/2410.10626v1.
24. Wang, J., Liu, Y. & Wang, X., 2021. Assessing Multilingual Fairness in Pre-trained Multimodal Representations. arXiv. Available at: http://arxiv.org/abs/2106.06683v2.
25. Kristanto, Y. & Padmi, R., 2020. Flipping A Statistics Classroom for Pre-Service English Language Teachers. arXiv. Available at: http://arxiv.org/abs/2002.05530v1.
26. Maddigan, P. & Susnjak, T., 2023. Chat2VIS: Fine-Tuning Data Visualisations using Multilingual Natural Language Text and Pre-Trained Large Language Models. arXiv. Available at: http://arxiv.org/abs/2303.14292v1.
27. Lugini, L. & Litman, D., 2019. Predicting Specificity in Classroom Discussion. arXiv. Available at: http://arxiv.org/abs/1909.01462v1.
28. Zhang, J. et al., 2024. Virbo: Multimodal Multilingual Avatar Video Generation in Digital Marketing. arXiv. Available at: http://arxiv.org/abs/2403.11700v2.
29. Demszky, D. & Hill, H., 2022. The NCTE Transcripts: A Dataset of Elementary Math Classroom Transcripts. arXiv. Available at: http://arxiv.org/abs/2211.11772v2.
30. Bouzoubaa, L., Aghakhani, E. & Rezapour, R., 2024. Words Matter: Reducing Stigma in Online Conversations about Substance Use with Large Language Models. arXiv. Available at: http://arxiv.org/abs/2408.07873v1.
31. Lyons, D., Zahra, S. & Marshall, T., 2019. Towards Lakosian Multilingual Software Design Principles. arXiv. Available at: http://arxiv.org/abs/1906.08351v1.

32. Chen, N. et al., 2023. Breaking Language Barriers in Multilingual Mathematical Reasoning: Insights and Observations. arXiv. Available at: http://arxiv.org/abs/2310.20246v5.
33. V., J., Mondal, A. & Jawahar, C., 2022. Classroom Slide Narration System. arXiv. Available at: http://arxiv.org/abs/2201.08574v1.
34. Dhamecha, T. et al., 2021. Role of Language Relatedness in Multilingual Fine-tuning of Language Models: A Case Study in Indo-Aryan Languages. arXiv. Available at: http://arxiv.org/abs/2109.10534v1.
35. Steinberger, R., 2014. A survey of methods to ease the development of highly multilingual text mining applications. arXiv. Available at: http://arxiv.org/abs/1401.2937v1.
36. Zhang, Z. et al., 2024. Simulating Classroom Education with LLM-Empowered Agents. arXiv. Available at: http://arxiv.org/abs/2406.19226v1.
37. Ji, S. et al., 2024. Can Machine Translation Bridge Multilingual Pretraining and Cross-lingual Transfer Learning?. arXiv. Available at: http://arxiv.org/abs/2403.16777v1.
38. Miroyan, M. et al., 2023. EIT: Earnest Insight Toolkit for Evaluating Students' Earnestness in Interactive Lecture Participation Exercises. arXiv. Available at: http://arxiv.org/abs/2311.10746v1.
39. Chelombitko, I., Safronov, E. & Komissarov, A., 2024. Qtok: A Comprehensive Framework for Evaluating Multilingual Tokenizer Quality in Large Language Models. arXiv. Available at: http://arxiv.org/abs/2410.12989v1.
40. Lyons, D., Bogar, A. & Baird, D., 2018. Lightweight Multilingual Software Analysis. arXiv. Available at: http://arxiv.org/abs/1808.01210v1.
41. Gillis-Webber, F. & Keet, C., 2022. A Review of Multilingualism in and for Ontologies. arXiv. Available at: http://arxiv.org/abs/2210.02807v1.
42. Bogoychev, N. et al., 2023. OpusCleaner and OpusTrainer, open source toolkits for training Machine Translation and Large language models. arXiv. Available at: http://arxiv.org/abs/2311.14838v1.
43. Gong, H. et al., 2023. Multilingual Speech-to-Speech Translation into Multiple Target Languages. arXiv. Available at: http://arxiv.org/abs/2307.08655v1.
44. Chau, E. & Smith, N., 2021. Specializing Multilingual Language Models: An Empirical Study. arXiv. Available at: http://arxiv.org/abs/2106.09063v4.
45. Chang, T. et al., 2023. When Is Multilinguality a Curse? Language Modeling for 250 High- and Low-Resource Languages. arXiv. Available at: http://arxiv.org/abs/2311.09205v1.
46. Lin, N. et al., 2023. Model and Evaluation: Towards Fairness in Multilingual Text Classification. arXiv. Available at: http://arxiv.org/abs/2303.15697v1.
47. Tang, Z., Li, L. & Wang, D., 2016. Multi-task Recurrent Model for True Multilingual Speech Recognition. arXiv. Available at: http://arxiv.org/abs/1609.08337v1.

48. Shaham, U. et al., 2024. Multilingual Instruction Tuning With Just a Pinch of Multilinguality. arXiv. Available at: http://arxiv.org/abs/2401.01854v4.
49. Do, Q. et al., 2020. To What Degree Can Language Borders Be Blurred In BERT-based Multilingual Spoken Language Understanding?. arXiv. Available at: http://arxiv.org/abs/2011.05007v1.
50. Intrator, Y. et al., 2024. Breaking the Language Barrier: Can Direct Inference Outperform Pre-Translation in Multilingual LLM Applications?. arXiv. Available at: http://arxiv.org/abs/2403.04792v1.

3b: Can AI-powered tools reduce the language barrier in multilingual classrooms and foster inclusivity?

This literature review examines the potential of AI-powered tools to reduce language barriers and foster inclusivity in multilingual classrooms. Several studies highlight the promise of AI in various aspects of language learning and classroom management. One key area is personalized support for teachers. Handa et al. (2023) explored the use of large language models (LLMs) to provide automated coaching for teachers in using growth mindset supportive language (GMSL). Their findings suggest that LLM-generated feedback can be more effective than human feedback in promoting a growth mindset and encouraging students to embrace challenges, demonstrating the potential of LLMs to enhance teacher effectiveness and, consequently, student learning outcomes in diverse classrooms. Addressing the challenge of creating language-specific models from large multilingual models, Ushio et al. (2023) proposed a vocabulary-trimming method to reduce the size of multilingual language models while retaining performance. This approach allows for the creation of smaller, more efficient monolingual models from existing multilingual ones, potentially facilitating the development of language-specific tools for diverse classrooms.

Beyond teacher support, AI can also directly enhance the learning experience for students. Attia et al. (2024) investigated the use of continued pretraining to adapt automatic speech recognition (ASR) models to classroom environments. Their research demonstrated that this technique improves the robustness of ASR systems to various noises and microphone types commonly found in classrooms, paving the way for more effective use of voice-based AI tools in educational settings. Viberg and Kukulska-Hulme (2021) emphasized the importance of self-regulated and collaborative learning in language acquisition, particularly in mobile-assisted language learning environments. They suggest that advancements in AI and learning analytics can be leveraged to create personalized adaptive learning paths, catering to the diverse needs of language learners in and beyond the classroom.

Furthermore, AI can facilitate interactive learning experiences. Tan (2023) explored the use of LLMs for "flipped interaction" in classrooms, where LLMs generate questions rather than answers. This approach enhances traditional classroom flipping techniques like Peer Instruction and Just-in-Time Teaching, promoting student engagement and self-regulated learning. Their LLM-driven chatbot software facilitated the creation of student-generated questions and personalized learning pathways, demonstrating the potential of AI to foster interactive learning in diverse classroom settings. Finally, Wu (2023) addressed the challenge of limited multilingual image captions in vision-and-language research. Their proposed ICU (Image Caption Understanding) framework utilizes a two-stage approach, leveraging English image captioning followed by cross-lingual understanding with a multilingual language model. This method overcomes the scarcity of multilingual data and facilitates cross-lingual image understanding, potentially opening up new avenues for multimodal learning in multilingual classrooms. In conclusion, these studies collectively demonstrate the potential of AI-powered tools to address the language barrier and promote inclusivity in multilingual classrooms by supporting teachers, personalizing learning experiences, and fostering interactive learning environments.

Can AI-powered tools reduce the language barrier in multilingual classrooms and foster inclusivity? This research question sits at the intersection of artificial intelligence, education, and sociolinguistics, demanding a nuanced understanding of both the capabilities and limitations of current AI technologies. Several recent studies offer valuable insights into this complex issue.

One key area of exploration lies in the crosslingual capabilities of Large Language Models (LLMs). While LLMs are trained on vast multilingual corpora, their ability to genuinely relate concepts across languages remains a challenge. Chua et al. (2024) investigated the crosslingual knowledge transfer abilities of several state-of-the-art LLMs and found that while they excel at surface-level tasks like machine translation, they struggle with deeper crosslingual knowledge transfer. This "crosslingual knowledge barrier" suggests that simply deploying existing LLMs in multilingual classrooms may not be sufficient to bridge the language gap. Their research highlights the need for explicit optimization and fine-tuning on mixed-language data to unlock the full potential of LLMs for crosslingual understanding.

Beyond LLMs, other AI tools are being explored for their potential to enhance inclusivity in diverse learning environments. Campos and Couto (2017) developed the Multilingual Report Annotator (MRA), a web application designed to translate and annotate radiology reports. This work demonstrates the potential of AI to overcome language barriers in specialized domains, offering a potential model for similar applications in education. By translating specialized educational materials, such tools could make complex subjects accessible to students from diverse linguistic backgrounds.

The specific challenges of classroom environments also require tailored AI solutions. Attia et al. (2024) explored the use of continued pretraining (CPT) to adapt Wav2vec2.0, an automatic speech recognition (ASR) model, to the noisy and diverse acoustic conditions of classrooms. Their findings demonstrate that CPT significantly improves the robustness of ASR systems to different noises, microphones, and classroom demographics, paving the way for more effective voice-based AI tools in educational settings. This improved robustness is crucial for ensuring that AI-powered transcription and translation tools can accurately capture and interpret student contributions in multilingual classrooms.

Furthermore, the integration of AI into pedagogical practices requires careful consideration of the learner-AI interaction. Kumar et al. (2023) investigated the impact of different guidance strategies on student interaction with LLM-based chatbot teaching assistants. Their findings highlight the importance of pedagogical design in shaping how students engage with AI tools, emphasizing that simply providing access to LLMs is not enough. Instead, teachers must play an active role in structuring the learning environment and guiding student interactions with AI to maximize learning outcomes and build trust in these tools.

The potential benefits of AI extend beyond language learning to supporting students with diverse learning needs. Yang et al. (2024) explored the use of the NAO robot in a special education classroom for students with Autism Spectrum Disorder (ASD). Their findings suggest that the robot's presence enhanced student engagement and reduced stereotypical repetitive behaviors, demonstrating the potential of AI-powered tools to create more inclusive and supportive learning environments for students with disabilities. This research underscores the potential of AI to personalize learning experiences and cater to the unique needs of individual learners.

Finally, it's crucial to acknowledge the potential biases embedded within multilingual language models. Papadimitriou et al. (2022) investigated the phenomenon of "grammatical structure bias," where grammatical structures from higher-resource languages bleed into lower-resource languages in multilingual models. This research highlights the importance of carefully evaluating and mitigating biases in AI tools to ensure equitable outcomes for all learners. Failing to address these biases could exacerbate existing inequalities and undermine the goal of fostering inclusivity in multilingual classrooms.

In conclusion, while AI-powered tools hold significant promise for reducing language barriers and fostering inclusivity in multilingual classrooms, their effective implementation requires careful consideration of their limitations, potential biases, and the pedagogical context in which they are deployed. Further research is needed to develop and evaluate AI tools that are specifically designed to address the complex challenges of multilingual learning environments and to ensure that these tools are used in ways that promote equitable and inclusive educational outcomes for all students.
The question of whether AI-powered tools can reduce language barriers in multilingual classrooms and foster inclusivity is gaining increasing attention in educational research. Several studies explore the potential of AI to bridge communication gaps and create more equitable learning environments. Molina et al. (2024) investigated the use of an LLM tutor in an introductory computing course, finding that while Non-Native English Speaking (NNES) students utilized the tool less frequently than their native-speaking counterparts, they appreciated its accessibility and ability to bypass the need for perfect English communication. This suggests that LLM tutors can offer tailored support and overcome language barriers, particularly in technically demanding subjects. Beyond language tutoring, AI is being explored in other educational contexts. Karagounis (2023) examined the potential of simulation robotics as an interactive learning experience, highlighting its ability to engage students in hands-on STEM learning, which can transcend language differences through shared activity and visual representation.

Addressing communication barriers directly, Moryossef (2023) introduced sign.mt, an open-source application for real-time multilingual translation between spoken and signed languages. This tool aims to bridge the communication divide between hearing and deaf individuals, promoting inclusivity by facilitating seamless bidirectional translation and offering customizable avatars for a more personalized experience. While sign.mt represents a significant step towards accessible communication, the authors encourage further development and community contributions to enhance its capabilities. The development of effective multilingual AI models themselves presents challenges. Tan et al. (2024) explored the issue of negative interference in unified multilingual models, proposing a "Neuron Specialization" approach to modularize feed-forward layers and reduce interference while promoting knowledge transfer. This research highlights the complexities of building truly multilingual AI systems that can effectively serve diverse language communities.

Further emphasizing the importance of multilingual capabilities, Liu et al. (2024) focused on the truthfulness of Multilingual Large Language Models (MLLMs). They developed a benchmark for truthfulness evaluation and proposed a method to align facts across languages, aiming to reduce representation disparity and enhance the overall reliability of MLLMs across different languages. This work underscores the need for rigorous evaluation and development strategies to ensure that AI tools provide accurate and equitable information access in multilingual settings. Finally, Long and Zhang (2024) investigated the use of AI to analyze classroom dialogue, developing an agent that combines expert-informed rule-based systems with an LLM. This agent can categorize dialogue sequences, offering a scalable and efficient method for analyzing classroom interactions and potentially improving teaching practices. This research demonstrates the potential of AI to not only bridge language barriers but also to provide valuable insights into the dynamics of multilingual classrooms, ultimately contributing to a more inclusive and effective learning environment.

Literature Review: This literature review examines the potential of AI-powered tools to reduce language barriers and foster inclusivity in multilingual classrooms. Several studies highlight the promise of AI in various aspects of language learning and classroom management. One key area is personalized support for teachers. Handa et al. (2023) explored the use of large language models (LLMs) to provide automated coaching for teachers in using growth mindset supportive language (GMSL). Their findings suggest that LLM-generated feedback can be more effective than human feedback in promoting a growth mindset and encouraging students to embrace challenges, demonstrating the potential of LLMs to enhance teacher effectiveness and, consequently, student learning outcomes in diverse classrooms. Addressing the challenge of creating language-specific models from large multilingual models, Ushio et al. (2023) proposed a vocabulary-trimming method to reduce the size of multilingual language models while retaining performance. This approach allows for the creation of smaller, more efficient monolingual models from existing multilingual ones, potentially facilitating the development of language-specific tools for diverse classrooms.

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The potential benefits of AI extend beyond language learning to supporting students with diverse learning needs. Yang et al. (2024) explored the use of the NAO robot in a special education classroom for students with Autism Spectrum Disorder (ASD). Their findings suggest that the robot's presence enhanced student engagement and reduced stereotypical repetitive behaviors, demonstrating the potential of AI-powered tools to create more inclusive and supportive learning environments for students with disabilities. This research underscores the potential of AI to personalize learning experiences and cater to the unique needs of individual learners.

Finally, it's crucial to acknowledge the potential biases embedded within multilingual language models. Papadimitriou et al. (2022) investigated the phenomenon of "grammatical structure bias," where grammatical structures from higher-resource languages bleed into lower-resource languages in multilingual models. This research highlights the importance of carefully evaluating and mitigating biases in AI tools to ensure equitable outcomes for all learners. Failing to address these biases could exacerbate existing inequalities and undermine the goal of fostering inclusivity in multilingual classrooms.

In conclusion, while AI-powered tools hold significant promise for reducing language barriers and fostering inclusivity in multilingual classrooms, their effective implementation requires careful consideration of their limitations, potential biases, and the pedagogical context in which they are deployed. Further research is needed to develop and evaluate AI tools that are specifically designed to address the complex challenges of multilingual learning environments and to ensure that these tools are used in ways that promote equitable and inclusive educational outcomes for all students.
The question of whether AI-powered tools can reduce language barriers in multilingual classrooms and foster inclusivity is gaining increasing attention in educational research. Several studies explore the potential of AI to bridge communication gaps and create more equitable learning environments. Molina et al. (2024) investigated the use of an LLM tutor in an introductory computing course, finding that while Non-Native English Speaking (NNES) students utilized the tool less frequently than their native-speaking counterparts, they appreciated its accessibility and ability to bypass the need for perfect English communication. This suggests that LLM tutors can offer tailored support and overcome language barriers, particularly in technically demanding subjects. Beyond language tutoring, AI is being explored in other educational contexts. Karagounis (2023) examined the potential of simulation robotics as an interactive learning experience, highlighting its ability to engage students in hands-on STEM learning, which can transcend language differences through shared activity and visual representation.

Addressing communication barriers directly, Moryossef (2023) introduced sign.mt, an open-source application for real-time multilingual translation between spoken and signed languages. This tool aims to bridge the communication divide between hearing and deaf individuals, promoting inclusivity by facilitating seamless bidirectional translation and offering customizable avatars for a more personalized experience. While sign.mt represents a significant step towards accessible communication, the authors encourage further development and community contributions to enhance its capabilities. The development of effective multilingual AI models themselves presents challenges. Tan et al. (2024) explored the issue of negative interference in unified multilingual models, proposing a "Neuron Specialization" approach to modularize feed-forward layers and reduce interference while promoting knowledge transfer. This research highlights the complexities of building truly multilingual AI systems that can effectively serve diverse language communities.

Further emphasizing the importance of multilingual capabilities, Liu et al. (2024) focused on the truthfulness of Multilingual Large Language Models (MLLMs). They developed a benchmark for truthfulness evaluation and proposed a method to align facts across languages, aiming to reduce representation disparity and enhance the overall reliability of MLLMs across different languages. This work underscores the need for rigorous evaluation and development strategies to ensure that AI tools provide accurate and equitable information access in multilingual settings. Finally, Long and Zhang (2024) investigated the use of AI to analyze classroom dialogue, developing an agent that combines expert-informed rule-based systems with an LLM. This agent can categorize dialogue sequences, offering a scalable and efficient method for analyzing classroom interactions and potentially improving teaching practices. This research demonstrates the potential of AI to not only bridge language barriers but also to provide valuable insights into the dynamics of multilingual classrooms, ultimately contributing to a more inclusive and effective learning environment.

References:

1. Handa, K. et al., 2023. "Mistakes Help Us Grow": Facilitating and Evaluating Growth Mindset Supportive Language in Classrooms. arXiv. Available at: http://arxiv.org/abs/2310.10637v1.
2. Ushio, A., Zhou, Y. & Camacho-Collados, J., 2023. An Efficient Multilingual Language Model Compression through Vocabulary Trimming. arXiv. Available at: http://arxiv.org/abs/2305.15020v3.
3. Attia, A. et al., 2024. CPT-Boosted Wav2vec2.0: Towards Noise Robust Speech Recognition for Classroom Environments. arXiv. Available at: http://arxiv.org/abs/2409.14494v1.
4. Viberg, O. & Kukulska-Hulme, A., 2021. Fostering learners' self-regulation and collaboration skills and strategies for mobile language learning beyond the classroom. arXiv. Available at: http://arxiv.org/abs/2104.12486v1.
5. Tan, C., 2023. Large Language Model-Driven Classroom Flipping: Empowering Student-Centric Peer Questioning with Flipped Interaction. arXiv. Available at: http://arxiv.org/abs/2311.14708v1.
6. Wu, G., 2023. ICU: Conquering Language Barriers in Vision-and-Language Modeling by Dividing the Tasks into Image Captioning and Language Understanding. arXiv. Available at: http://arxiv.org/abs/2310.12531v3.
7. Chua, L. et al., 2024. Crosslingual Capabilities and Knowledge Barriers in Multilingual Large Language Models. arXiv. Available at: http://arxiv.org/abs/2406.16135v1.
8. Yang, Q. et al., 2024. Surprising Performances of Students with Autism in Classroom with NAO Robot. arXiv. Available at: http://arxiv.org/abs/2407.12014v1.
9. Campos, L. & Couto, F., 2017. MRA - Proof of Concept of a Multilingual Report Annotator Web Application. arXiv. Available at: http://arxiv.org/abs/1704.01748v3.

10. Attia, A. et al., 2024. Continued Pretraining for Domain Adaptation of Wav2vec2.0 in Automatic Speech Recognition for Elementary Math Classroom Settings. arXiv. Available at: http://arxiv.org/abs/2405.13018v1.
11. Kumar, H. et al., 2023. Impact of Guidance and Interaction Strategies for LLM Use on Learner Performance and Perception. arXiv. Available at: http://arxiv.org/abs/2310.13712v3.
12. Papadimitriou, I., Lopez, K. & Jurafsky, D., 2022. Multilingual BERT has an accent: Evaluating English influences on fluency in multilingual models. arXiv. Available at: http://arxiv.org/abs/2210.05619v2.
13. Molina, I. et al., 2024. Leveraging LLM Tutoring Systems for Non-Native English Speakers in Introductory CS Courses. arXiv. Available at: http://arxiv.org/abs/2411.02725v1.
14. Karagounis, A., 2023. Robotics as a Simulation Educational Tool. arXiv. Available at: http://arxiv.org/abs/2312.05582v1.
15. Moryossef, A., 2023. sign.mt: Real-Time Multilingual Sign Language Translation Application. arXiv. Available at: http://arxiv.org/abs/2310.05064v2.
16. Tan, S., Wu, D. & Monz, C., 2024. Neuron Specialization: Leveraging intrinsic task modularity for multilingual machine translation. arXiv. Available at: http://arxiv.org/abs/2404.11201v1.
17. Liu, W. et al., 2024. Towards Truthful Multilingual Large Language Models: Benchmarking and Alignment Strategies. arXiv. Available at: http://arxiv.org/abs/2406.14434v1.
18. Long, Y. & Zhang, Y., 2024. Enhanced Classroom Dialogue Sequences Analysis with a Hybrid AI Agent: Merging Expert Rule-Base with Large Language Models. arXiv. Available at: http://arxiv.org/abs/2411.08418v1.
19. Blevins, T. et al., 2024. Breaking the Curse of Multilinguality with Cross-lingual Expert Language Models. arXiv. Available at: http://arxiv.org/abs/2401.10440v2.
20. Das, B. et al., 2024. Explainable Artificial Intelligence for Quantifying Interfering and High-Risk Behaviors in Autism Spectrum Disorder in a Real-World Classroom Environment Using Privacy-Preserving Video Analysis. arXiv. Available at: http://arxiv.org/abs/2407.21691v1.
Execution time: 55.055466651916504

4a: What role can AI play in reducing teacher workload through automated grading and feedback?

Execution time: 80.85

The role of AI in reducing teacher workload through automated grading and feedback is a burgeoning area of research with significant potential to reshape educational practices. This literature review examines this potential through the lens of various studies exploring AI's capabilities and limitations in educational settings.

Several studies highlight the potential of AI to automate administrative tasks, thereby freeing up teachers' time for more impactful interactions with students. Oh and Ahn (2024) explored teachers' perceptions of AI in South Korea, finding that educators anticipate AI's potential to complement their work by automating administrative burdens and personalizing learning. Similarly, Bhowmick et al. (2023) designed an automated question generation tool, demonstrating through an expert survey that such tools can significantly reduce teacher workload and personalize learning experiences. This need for automation in education is further emphasized by Colombo et al. (2024), who analyzed the potential for AI to automate job-related tasks, finding that a significant portion of tasks, including those in education, are highly exposed to automation. The automation of repetitive work in creative domains is explored by Thasarathan and Ebrahimi (2020), focusing on line art colorization in animation. This automation has implications for education as well, especially in areas like visual arts and design.

Beyond simply automating tasks, AI offers opportunities to enhance the quality and efficiency of grading itself. Kortemeyer and Nöhl (2024) investigated AI's application in grading high-stakes physics exams, demonstrating its potential to achieve high accuracy while significantly reducing grading workloads. Gobrecht et al. (2024) developed an automatic short answer grading (ASAG) system and found that it performed with greater consistency than human graders, suggesting potential for increased fairness through reduced subjectivity. Sonkar et al. (2024) introduced a novel "Marking" task that involves detailed analysis and visual feedback on student responses, moving beyond binary grading. This work highlights the potential for AI to offer more nuanced and informative feedback than traditional methods.

Furthermore, AI can facilitate interactive and personalized feedback, addressing a critical need in education. Hong et al. (2024) introduced CAELF, an AI-powered framework for automating interactive feedback, allowing students to query and challenge feedback, significantly improving the reasoning and interaction capabilities of LLMs. Yao et al. (2021) designed an automated question-answer generation system, which could be used by teachers to assess student comprehension skills and personalize learning experiences. This system addresses the need for educators to efficiently gauge student understanding and tailor their teaching accordingly. Farhana et al. (2024) introduced SimPal, an LLM-based agent that helps teachers align existing AI agents in simulations with their evolving pedagogical goals, addressing the challenge of integrating third-party educational tools.

However, the integration of AI in education also presents challenges and necessitates careful consideration of teachers' perspectives and concerns. Chan and Tsi (2023) examined the potential of AI to replace or assist teachers in higher education, finding that while AI can enhance teaching, human qualities remain irreplaceable. Daskalaki et al. (2024) conducted a cross-national study on teachers' perspectives on AI in education, highlighting concerns about critical thinking development and ethical implications, as well as a need for professional development. Viberg et al. (2023) investigated teacher trust in AI-EdTech, finding that self-efficacy and understanding of AI are key factors influencing adoption. Cukurova et al. (2023) similarly emphasized the importance of factors such as reducing workload, increasing teacher ownership, and addressing ethical concerns for successful AI adoption in schools. These studies underscore the need for a human-centered approach to AI integration in education.

Beyond teacher perspectives, practical and technical considerations also shape AI's role in education. Mulian et al. (2023) examined the potential of AI in teaching motor skills, highlighting the potential of reinforcement learning and imitation learning models. Tong et al. (2024) utilized AIoT technology for automated poultry health monitoring, demonstrating the potential of edge-AI enabled systems. This work, while outside of the traditional classroom, demonstrates the broader applicability of AI in automating tasks, which could have implications for school management and operations. Fu et al. (2023) developed GPT4AIGChip, a framework leveraging LLMs for automated AI accelerator design, highlighting the potential of AI to aid in the development of specialized hardware for educational AI applications. Mars (2022) advocated for a re-envisioning of the system stack from the programming language level down to address the complexity of AI integration.

Moreover, research on human-AI interaction in various contexts informs the development of effective AI tools for education. Lubars and Tan (2019) explored human preferences for AI automation across tasks, finding a strong preference for machine-in-the-loop designs. Haensch et al. (2023) analyzed TikTok content on ChatGPT, revealing student perceptions and uses of the tool, highlighting the need for educators to understand student engagement with AI. Ghai et al. (2020) investigated the use of AI explanations in active learning for machine teaching, demonstrating the potential and drawbacks of explainable AI in educational settings. Kandasamy (2024) explored ethical leadership in the age of AI, emphasizing the importance of addressing ethical challenges and leveraging opportunities presented by AI. These studies highlight the need to understand human interaction with AI and design systems that promote trust, transparency, and ethical use.

Additional research explores broader contexts and applications of AI that can inform its integration in education. Huang (2024) investigated AI for automating medical report generation for retinal images, demonstrating its potential to improve efficiency and accuracy in a specialized field. Gavade et al. (2023) studied sociotechnical support infrastructures for teachers, highlighting the importance of support systems for teacher well-being, a factor that should be considered when implementing AI tools that might impact teacher roles and workload. Ding et al. (2022) proposed Stochastic Knowledge Distillation for obtaining compact language models, which could be beneficial for developing efficient AI-powered educational tools. Hao et al. (2020) developed a workload allocation method for AI in distributed computing systems, demonstrating potential optimizations for resource management in AI-powered educational platforms. Forero and Herrera-Suárez (2023) investigated the influence of ChatGPT on student performance in physics, highlighting the need for cautious and reflective use of AI tools in education. Zhu et al. (2021) argued that games are an ideal domain for studying human-AI interaction, offering insights for designing engaging and effective AI-powered educational games. Alenezi et al. (2022) explored the transformation of DevOps by AI, highlighting the potential for AI to improve software development processes, which could be relevant for developing and maintaining AI-EdTech platforms. Sridharan et al. (2023) proposed Chakra, an open graph schema for standardizing workload specification, which could facilitate the development of benchmarks and simulators for AI systems in education. D. et al. et al. (2018) discussed many-core co-design and the importance of customizable workload generators for benchmarking, which could inform the design of hardware and software for AI in education. Avin et al. (2019) presented a role-play game for exploring the impacts of AI, offering a novel approach to teaching and understanding the societal and ethical implications of AI. Rausch et al. (2020) developed a simulation-based environment for evaluating operational strategies for AI workflow systems, which could be applied to educational AI platforms. Heim et al. (2024) argued for the role of compute providers in AI regulation, highlighting the importance of responsible AI development and deployment, which is crucial for educational applications. Sawczyn et al. (2024) introduced a semi-automated approach for creating datasets for low-resource languages, which could facilitate the development of AI-powered educational tools for diverse linguistic communities. Susanto et al. (2023) explored the use of language models in creative writing, demonstrating AI's potential to support creative activities, which could be integrated into educational settings. Csernoch et al. (2024) investigated the use of spreadsheets for teaching traditional tasks, demonstrating the potential of existing digital tools in education. Martinez (2022) studied the effects of teachers' stereotypical assessments on student outcomes, highlighting the importance of fairness and equity in education, which should be considered when designing AI-powered assessment tools. Cardenal et al. (2024) examined the relationship between teaching styles and teacher-student relationships, highlighting the importance of considering the impact of AI tools on these dynamics. Nyaaba (2024) explored the potential of GenAI in teacher education in developing countries, focusing on its capacity to support content knowledge acquisition and free up teacher educators to focus on pedagogical modeling and other critical areas. Akash et al. (2020) presented a framework for calibrating human trust in automation, which is crucial for designing effective human-AI collaboration in educational contexts. Finally, Cath and Jansen (2021) discussed the use of AI registers as a governance model, highlighting the importance of responsible and transparent AI implementation in public services, including education. Gordienko and Schnabel (2017) discussed the importance of explainability in AI for shifting human roles from data annotators to collaborators, a shift that is also relevant for the use of AI in education. Michael (2021) exemplified the role of explainability in AI, further reinforcing the need for transparency in AI systems used in educational settings. Gordienko and Schnabel (2018) investigated weak equivalence of gradings in algebras, offering insights into the theoretical foundations of grading systems, which could inform the design of AI-powered grading tools. Magoulianitis et al. (2023) reviewed AI approaches to nuclei segmentation in digital pathology, highlighting the importance of efficient and explainable AI models in healthcare, principles that also apply to educational AI applications. Chignell et al. (2024) introduced an AI Mastery Lifecycle framework for human-AI interaction, providing guidance on task allocation and interface design, which is relevant for the integration of AI in education. Agrawal et al. (2023) proposed a framework for understanding the roles and automation levels of Digital Twins in work systems, offering insights that can be applied to the design and implementation of AI-powered educational tools. Montalbano and Benedetti (2013) reported on a course designed to demonstrate active learning in physics, highlighting the importance of effective teacher training for integrating new technologies like AI into educational practices.

In conclusion, the research suggests that AI has the potential to significantly reduce teacher workload through automated grading and feedback, while also enhancing the quality and personalization of learning experiences. However, successful integration requires careful consideration of teacher perspectives, ethical implications, and the development of robust and transparent AI systems that complement human educators rather than replace them. Further research is needed to address the challenges and fully realize the potential of AI to transform education.

References:

1. Oh, S.-. young . & Ahn, Y., 2024. Exploring Teachers' Perception of Artificial Intelligence: The Socio-emotional Deficiency as Opportunities and Challenges in

Human-AI Complementarity in K-12 Education. arXiv. Available at: http://arxiv.org/abs/2405.13065v1.
2. Kortemeyer, G. & Nöhl, J., 2024. Assessing Confidence in AI-Assisted Grading of Physics Exams through Psychometrics: An Exploratory Study. arXiv. Available at: http://arxiv.org/abs/2410.19409v1.
3. Mulian, H. et al., 2023. Mimicking the Maestro: Exploring the Efficacy of a Virtual AI Teacher in Fine Motor Skill Acquisition. arXiv. Available at: http://arxiv.org/abs/2310.10280v2.
4. Chan, C. & Tsi, L., 2023. The AI Revolution in Education: Will AI Replace or Assist Teachers in Higher Education?. arXiv. Available at: http://arxiv.org/abs/2305.01185v1.
5. Tong, Q. et al., 2024. Edge AI-Enabled Chicken Health Detection Based on Enhanced FCOS-Lite and Knowledge Distillation. arXiv. Available at: http://arxiv.org/abs/2407.09562v3.
6. Bhowmick, A. et al., 2023. Automating question generation from educational text. arXiv. Available at: http://arxiv.org/abs/2309.15004v1.
7. Colombo, E. et al., 2024. Towards the Terminator Economy: Assessing Job Exposure to AI through LLMs. arXiv. Available at: http://arxiv.org/abs/2407.19204v1.
8. Zhai, X., 2024. Transforming Teachers' Roles and Agencies in the Era of Generative AI: Perceptions, Acceptance, Knowledge, and Practices. arXiv. Available at: http://arxiv.org/abs/2410.03018v1.
9. Hong, S. et al., 2024. "My Grade is Wrong!": A Contestable AI Framework for Interactive Feedback in Evaluating Student Essays. arXiv. Available at: http://arxiv.org/abs/2409.07453v1.
10. Gobrecht, A. et al., 2024. Beyond human subjectivity and error: a novel AI grading system. arXiv. Available at: http://arxiv.org/abs/2405.04323v1.
11. Daskalaki, E., Psaroudaki, K. & Fragopoulou, P., 2024. Navigating the Future of Education: Educators' Insights on AI Integration and Challenges in Greece, Hungary, Latvia, Ireland and Armenia. arXiv. Available at: http://arxiv.org/abs/2408.15686v1.
12. Viberg, O. et al., 2023. What Explains Teachers' Trust of AI in Education across Six Countries?. arXiv. Available at: http://arxiv.org/abs/2312.01627v2.
13. Huang, J.-H., 2024. Automated Retinal Image Analysis and Medical Report Generation through Deep Learning. arXiv. Available at: http://arxiv.org/abs/2408.07349v1.
14. Gavade, A., Sidotam, A. & Varanasi, R., 2023. Pandemic, Hybrid Teaching & Stress: Examining Indian Teachers' Sociotechnical Support Practices in Low-income Schools. arXiv. Available at: http://arxiv.org/abs/2307.10220v1.
15. Fu, Y. et al., 2023. GPT4AIGChip: Towards Next-Generation AI Accelerator Design Automation via Large Language Models. arXiv. Available at: http://arxiv.org/abs/2309.10730v1.

16. Mars, J., 2022. The Case for a Wholistic Serverless Programming Paradigm and Full Stack Automation for AI and Beyond -- The Philosophy of Jaseci and Jac. arXiv. Available at: http://arxiv.org/abs/2206.08434v1.
17. Lubars, B. & Tan, C., 2019. Ask Not What AI Can Do, But What AI Should Do: Towards a Framework of Task Delegability. arXiv. Available at: http://arxiv.org/abs/1902.03245v2.
18. Haensch, A.-C. et al., 2023. Seeing ChatGPT Through Students' Eyes: An Analysis of TikTok Data. arXiv. Available at: http://arxiv.org/abs/2303.05349v1.
19. Ghai, B. et al., 2020. Explainable Active Learning (XAL): An Empirical Study of How Local Explanations Impact Annotator Experience. arXiv. Available at: http://arxiv.org/abs/2001.09219v4.
20. Kandasamy, U., 2024. Ethical Leadership in the Age of AI Challenges, Opportunities and Framework for Ethical Leadership. arXiv. Available at: http://arxiv.org/abs/2410.18095v2.
21. Cukurova, M., Miao, X. & Brooker, R., 2023. Adoption of Artificial Intelligence in Schools: Unveiling Factors Influencing Teachers Engagement. arXiv. Available at: http://arxiv.org/abs/2304.00903v2.
22. Yao, B. et al., 2021. It is AI's Turn to Ask Humans a Question: Question-Answer Pair Generation for Children's Story Books. arXiv. Available at: http://arxiv.org/abs/2109.03423v4.
23. Ding, Z. et al., 2022. SKDBERT: Compressing BERT via Stochastic Knowledge Distillation. arXiv. Available at: http://arxiv.org/abs/2211.14466v2.
24. Hao, T. et al., 2020. AI-oriented Medical Workload Allocation for Hierarchical Cloud/Edge/Device Computing. arXiv. Available at: http://arxiv.org/abs/2002.03493v1.
25. Forero, M. & Herrera-Suárez, H., 2023. ChatGPT in the Classroom: Boon or Bane for Physics Students' Academic Performance?. arXiv. Available at: http://arxiv.org/abs/2312.02422v1.
26. Zhu, J. et al., 2021. Player-AI Interaction: What Neural Network Games Reveal About AI as Play. arXiv. Available at: http://arxiv.org/abs/2101.06220v2.
27. Alenezi, M., Zarour, M. & Akour, M., 2022. Can Artificial Intelligence Transform DevOps?. arXiv. Available at: http://arxiv.org/abs/2206.00225v1.
28. Sridharan, S. et al., 2023. Chakra: Advancing Performance Benchmarking and Co-design using Standardized Execution Traces. arXiv. Available at: http://arxiv.org/abs/2305.14516v2.
29. D. et al., 2018. Consolidating the innovative concepts towards Exascale computing for Co-Design of Co-Applications ll: Co-Design Automation - Workload Characterization. arXiv. Available at: http://arxiv.org/abs/1806.01104v1.
30. Avin, S., Gruetzemacher, R. & Fox, J., 2019. Exploring AI Futures Through Role Play. arXiv. Available at: http://arxiv.org/abs/1912.08964v1.

31. Farhana, E. et al., 2024. SimPal: Towards a Meta-Conversational Framework to Understand Teacher's Instructional Goals for K-12 Physics. arXiv. Available at: http://arxiv.org/abs/2407.06241v1.
32. Rausch, T., Hummer, W. & Muthusamy, V., 2020. PipeSim: Trace-driven Simulation of Large-Scale AI Operations Platforms. arXiv. Available at: http://arxiv.org/abs/2006.12587v1.
33. Heim, L. et al., 2024. Governing Through the Cloud: The Intermediary Role of Compute Providers in AI Regulation. arXiv. Available at: http://arxiv.org/abs/2403.08501v2.
34. Sawczyn, A. et al., 2024. Developing PUGG for Polish: A Modern Approach to KBQA, MRC, and IR Dataset Construction. arXiv. Available at: http://arxiv.org/abs/2408.02337v1.
35. Susanto, H., Woo, D. & Guo, K., 2023. The Role of AI in Human-AI Creative Writing for Hong Kong Secondary Students. arXiv. Available at: http://arxiv.org/abs/2304.11276v1.
36. Csernoch, M., Gulácsi, Á. & Csernoch, J., 2024. Subject integration with spreadsheets -- Ignoring education is the greatest risk ever. arXiv. Available at: http://arxiv.org/abs/2409.12975v1.
37. Sonkar, S. et al., 2024. Marking: Visual Grading with Highlighting Errors and Annotating Missing Bits. arXiv. Available at: http://arxiv.org/abs/2404.14301v1.
38. Martinez, J., 2022. The Long-Term Effects of Teachers' Gender Stereotypes. arXiv. Available at: http://arxiv.org/abs/2212.08220v2.
39. Cardenal, M.-E., Diaz-Santana, O.-D. & Gonzalez-Betancor, S.-M., 2024. Teacher-student relationship and teaching styles in primary education. A model of analysis. arXiv. Available at: http://arxiv.org/abs/2409.06562v1.
40. Nyaaba, M., 2024. Transforming Teacher Education in Developing Countries: The Role of Generative AI in Bridging Theory and Practice. arXiv. Available at: http://arxiv.org/abs/2411.10718v2.
41. Akash, K. et al., 2020. Human Trust-based Feedback Control: Dynamically varying automation transparency to optimize human-machine interactions. arXiv. Available at: http://arxiv.org/abs/2006.16353v1.
42. Cath, C. & Jansen, F., 2021. Dutch Comfort: The limits of AI governance through municipal registers. arXiv. Available at: http://arxiv.org/abs/2109.02944v1.
43. Gordienko, A. & Schnabel, O., 2017. On weak equivalences of gradings. arXiv. Available at: http://arxiv.org/abs/1704.07170v2.
44. Michael, L., 2021. Explainability and the Fourth AI Revolution. arXiv. Available at: http://arxiv.org/abs/2111.06773v1.
45. Montalbano, V. & Benedetti, R., 2013. Active learning in pre-service science teacher education. arXiv. Available at: http://arxiv.org/abs/1310.2982v3.

46. Thasarathan, H. & Ebrahimi, M., 2020. Artist-Guided Semiautomatic Animation Colorization. arXiv. Available at: http://arxiv.org/abs/2006.13717v2.
47. Gordienko, A. & Schnabel, O., 2018. Categories and weak equivalences of graded algebras. arXiv. Available at: http://arxiv.org/abs/1805.04073v2.
48. Magoulianitis, V., Alexander, C. & Kuo, C., 2023. A Comprehensive Overview of Computational Nuclei Segmentation Methods in Digital Pathology. arXiv. Available at: http://arxiv.org/abs/2308.08112v1.
49. Chignell, M. et al., 2024. The Model Mastery Lifecycle: A Framework for Designing Human-AI Interaction. arXiv. Available at: http://arxiv.org/abs/2408.12781v1.
50. Agrawal, A. et al., 2023. Digital Twin: Where do humans fit in?. arXiv. Available at: http://arxiv.org/abs/2301.03040v1.

4b: What role can AI play in reducing teacher workload through automated grading and feedback?

Execution time: 65.00

The role of AI in reducing teacher workload through automated grading and feedback is a burgeoning area of research with significant potential. Several studies highlight the multifaceted nature of this potential, ranging from automating administrative tasks to enhancing personalized learning. Oh and Ahn (2024) explored teachers' perceptions of AI's role in education, finding that educators anticipate AI's potential to complement their work by automating administrative tasks and personalizing learning. This highlights the perceived value of AI in streamlining teacher responsibilities, freeing up time for more direct student interaction. Focusing specifically on grading, Kortemeyer and Nöhl (2024) investigated the use of AI in grading high-stakes physics exams. Their findings demonstrate that AI can achieve high accuracy in grading, significantly reducing workload while maintaining precision, particularly when handling a portion of the grading load. This suggests that even partial automation of grading can yield substantial time savings for educators.

Beyond simply grading assessments, AI can also play a role in skill development. Mulian et al. (2023) examined the potential of a virtual AI teacher for motor skill acquisition, finding significant improvements in learner performance and the rate of skill acquisition. This research suggests that AI can personalize and optimize instruction in areas traditionally requiring significant teacher time and attention, such as handwriting practice. However, the integration of AI in education also raises important questions about the role of human teachers. Chan and Tsi (2023) explored the potential of AI to replace or assist teachers in higher education. Their study revealed that while some believe AI could eventually replace teachers, the majority of participants emphasized the irreplaceable qualities of human educators, such as critical thinking, creativity, and emotional intelligence. This underscores the importance of considering the unique contributions of human teachers alongside the potential benefits of AI.

While the focus on education is paramount, research in other fields offers valuable insights into the practical application of AI for workload reduction. Tong et al. (2024) demonstrated the successful implementation of an edge-AI system for automated poultry health monitoring, highlighting the potential of AI to automate complex tasks in real-world settings. This example, though outside the realm of education, showcases the feasibility and effectiveness of AI-driven automation in reducing human workload. Returning to the educational context, Bhowmick et al. (2023) investigated the automated generation of question-based activities (QBAs) for formative and summative assessment. Their research demonstrated the potential of AI to generate high-quality assessment materials, further reducing teacher workload and facilitating personalized learning experiences. This suggests that AI can not only automate grading but also assist in the creation of assessment materials, addressing a significant aspect of teacher workload. In summary, these studies collectively demonstrate the significant potential of AI to reduce teacher workload through automated grading and feedback, while also highlighting the importance of considering the unique contributions of human educators and the ethical implications of AI integration in education.

The role of AI in reducing teacher workload through automated grading and feedback is a burgeoning area of research with significant implications for the future of education. Several studies have explored different facets of this potential transformation. Colombo et al. (2024) developed a framework to assess the impact of AI on various job tasks, finding that a significant portion of employment, including high-skill jobs, is exposed to AI's influence, suggesting the potential for automation in education-related tasks as well. This potential for automation is further explored by Zhai (2024), who examined the evolving roles of teachers in the age of Generative AI (GenAI). This research proposes a framework categorizing teachers based on their level of GenAI engagement, from observers to innovators, highlighting the need for professional development and institutional support to facilitate effective GenAI integration in pedagogical practices.

The practical application of AI in automating feedback is addressed by Hong et al. (2024), who introduced CAELF, a framework utilizing a multi-agent system and computational argumentation to provide interactive feedback on student essays. This approach allows students to query and challenge AI-generated feedback, enhancing the reasoning and interaction capabilities of Large Language Models (LLMs) and potentially addressing the time constraints associated with traditional interactive feedback. Focusing specifically on automated grading, Gobrecht et al. (2024) developed an automatic short answer grading (ASAG) system based on a fine-tuned transformer model. Their findings suggest that this system can achieve high accuracy and even outperform human graders in consistency, potentially reducing subjectivity and increasing fairness in grading practices.

Beyond the technical aspects of AI integration, several studies have investigated teachers' perspectives and concerns. Daskalaki et al. (2024) conducted a cross-national study exploring teachers' understanding and use of AI in education. Their findings reveal a cautious optimism among educators, acknowledging AI's potential for personalized learning while expressing concerns about its impact on critical thinking and ethical implications. This cautious optimism is further explored by Viberg et al. (2023), who investigated the factors influencing teachers' trust in AI-EdTech. Their research highlights the importance of teacher self-efficacy and understanding of AI in fostering trust and promoting adoption in K-12 education, emphasizing the need for targeted professional development and consideration of cultural values. These studies collectively underscore the complex interplay between technological advancements, pedagogical practices, and teacher perceptions in realizing the potential of AI to reduce teacher workload and enhance educational outcomes.

The role of AI in reducing teacher workload through automated grading and feedback is a burgeoning area of research with significant potential. While much of the current AI research focuses on broader automation tasks, several studies offer insights into how this technology can be applied within the educational context. Lubars and Tan (2019) explore the human perception of task delegation to AI, highlighting the importance of factors like motivation, difficulty, risk, and trust. Their findings suggest a strong preference for human-in-the-loop systems, particularly in tasks requiring higher levels of trust, which has implications for the design of AI-powered grading and feedback systems that maintain teacher oversight and control. This preference for human involvement aligns with the findings of Gavade et al. (2023), who investigated the support systems available to teachers, particularly in low-income schools. Their research underscores the importance of sociotechnical support and the role of technology, like smartphones, in facilitating informal support networks. While not directly addressing AI, this study highlights the need for comprehensive support systems that incorporate both technological and human elements, suggesting that AI tools should be integrated within a broader framework of teacher support.

The potential of AI to automate complex tasks is evident in research from other domains. Huang (2024) demonstrates the application of AI in automating medical report generation for retinal images. This work showcases the ability of AI to analyze large datasets and identify subtle patterns, suggesting similar applications in educational settings for analyzing student work and providing personalized feedback.

Similarly, Fu et al. (2023) explore the use of large language models (LLMs) for automating AI accelerator design. Their GPT4AIGChip framework demonstrates the potential of LLMs to automate complex design processes through natural language instructions, hinting at the possibility of using LLMs to create customized grading rubrics and feedback mechanisms. Mars (2022) further emphasizes the potential of AI to automate complex systems through the development of the Jaseci system stack architecture and Jac programming language. This work highlights the ability of AI to handle diffuse sub-applications and inter-machine resources, suggesting its potential to manage the complexities of grading and feedback across diverse learning environments and platforms.

Finally, the rapid adoption and perception of AI tools like ChatGPT within the student population are crucial considerations. Haensch et al. (2023) analyze TikTok content related to ChatGPT, revealing how students utilize the tool for tasks like essay writing and code generation, as well as their awareness of AI detection mechanisms. This study underscores the need for educators to understand how students are already interacting with AI and to adapt their teaching and assessment strategies accordingly. The prevalence of discussions about circumventing AI detectors highlights the challenges in ensuring academic integrity in an AI-driven learning environment, further emphasizing the need for human oversight in automated grading and feedback systems. Therefore, while AI offers significant potential for automating grading and feedback, its implementation must consider the broader context of teacher support, student interaction with AI, and the ethical implications of automation in education.

Literature Review: The role of AI in reducing teacher workload through automated grading and feedback is a burgeoning area of research with significant potential. Several studies highlight the multifaceted nature of this potential, ranging from automating administrative tasks to enhancing personalized learning. Oh and Ahn (2024) explored teachers' perceptions of AI's role in education, finding that educators anticipate AI's potential to complement their work by automating administrative tasks and personalizing learning. This highlights the perceived value of AI in streamlining teacher responsibilities, freeing up time for more direct student interaction. Focusing specifically on grading, Kortemeyer and Nöhl (2024) investigated the use of AI in grading high-stakes physics exams. Their findings demonstrate that AI can achieve high accuracy in grading, significantly reducing workload while maintaining precision, particularly when handling a portion of the grading load. This suggests that even partial automation of grading can yield substantial time savings for educators.

Beyond simply grading assessments, AI can also play a role in skill development. Mulian et al. (2023) examined the potential of a virtual AI teacher for motor skill acquisition, finding significant improvements in learner performance and the rate of skill acquisition. This research suggests that AI can personalize and optimize instruction in areas traditionally requiring significant teacher time and attention, such as handwriting practice. However, the integration of AI in education also raises important questions about the role of human teachers. Chan and Tsi (2023) explored the potential of AI to replace or assist teachers in higher education. Their study revealed that while some believe AI could eventually replace teachers, the majority of participants emphasized the irreplaceable qualities of human educators, such as critical thinking, creativity, and emotional intelligence. This underscores the importance of considering the unique contributions of human teachers alongside the potential benefits of AI.

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References:

1. Oh, S.-. young . & Ahn, Y., 2024. Exploring Teachers' Perception of Artificial Intelligence: The Socio-emotional Deficiency as Opportunities and Challenges in Human-AI Complementarity in K-12 Education. arXiv. Available at: http://arxiv.org/abs/2405.13065v1.

2. Kortemeyer, G. & Nöhl, J., 2024. Assessing Confidence in AI-Assisted Grading of Physics Exams through Psychometrics: An Exploratory Study. arXiv. Available at: http://arxiv.org/abs/2410.19409v1.
3. Mulian, H. et al., 2023. Mimicking the Maestro: Exploring the Efficacy of a Virtual AI Teacher in Fine Motor Skill Acquisition. arXiv. Available at: http://arxiv.org/abs/2310.10280v2.
4. Chan, C. & Tsi, L., 2023. The AI Revolution in Education: Will AI Replace or Assist Teachers in Higher Education?. arXiv. Available at: http://arxiv.org/abs/2305.01185v1.
5. Tong, Q. et al., 2024. Edge AI-Enabled Chicken Health Detection Based on Enhanced FCOS-Lite and Knowledge Distillation. arXiv. Available at: http://arxiv.org/abs/2407.09562v3.
6. Bhowmick, A. et al., 2023. Automating question generation from educational text. arXiv. Available at: http://arxiv.org/abs/2309.15004v1.
7. Colombo, E. et al., 2024. Towards the Terminator Economy: Assessing Job Exposure to AI through LLMs. arXiv. Available at: http://arxiv.org/abs/2407.19204v1.
8. Zhai, X., 2024. Transforming Teachers' Roles and Agencies in the Era of Generative AI: Perceptions, Acceptance, Knowledge, and Practices. arXiv. Available at: http://arxiv.org/abs/2410.03018v1.
9. Hong, S. et al., 2024. "My Grade is Wrong!": A Contestable AI Framework for Interactive Feedback in Evaluating Student Essays. arXiv. Available at: http://arxiv.org/abs/2409.07453v1.
10. Gobrecht, A. et al., 2024. Beyond human subjectivity and error: a novel AI grading system. arXiv. Available at: http://arxiv.org/abs/2405.04323v1.
11. Daskalaki, E., Psaroudaki, K. & Fragopoulou, P., 2024. Navigating the Future of Education: Educators' Insights on AI Integration and Challenges in Greece, Hungary, Latvia, Ireland and Armenia. arXiv. Available at: http://arxiv.org/abs/2408.15686v1.
12. Viberg, O. et al., 2023. What Explains Teachers' Trust of AI in Education across Six Countries?. arXiv. Available at: http://arxiv.org/abs/2312.01627v2.
13. Huang, J.-H., 2024. Automated Retinal Image Analysis and Medical Report Generation through Deep Learning. arXiv. Available at: http://arxiv.org/abs/2408.07349v1.
14. Gavade, A., Sidotam, A. & Varanasi, R., 2023. Pandemic, Hybrid Teaching & Stress: Examining Indian Teachers' Sociotechnical Support Practices in Low-income Schools. arXiv. Available at: http://arxiv.org/abs/2307.10220v1.
15. Fu, Y. et al., 2023. GPT4AIGChip: Towards Next-Generation AI Accelerator Design Automation via Large Language Models. arXiv. Available at: http://arxiv.org/abs/2309.10730v1.
16. Mars, J., 2022. The Case for a Wholistic Serverless Programming Paradigm and Full Stack Automation for AI and Beyond -- The Philosophy of Jaseci and Jac. arXiv. Available at: http://arxiv.org/abs/2206.08434v1.

17. Lubars, B. & Tan, C., 2019. Ask Not What AI Can Do, But What AI Should Do: Towards a Framework of Task Delegability. arXiv. Available at: http://arxiv.org/abs/1902.03245v2.
18. Haensch, A.-C. et al., 2023. Seeing ChatGPT Through Students' Eyes: An Analysis of TikTok Data. arXiv. Available at: http://arxiv.org/abs/2303.05349v1.
19. Ghai, B. et al., 2020. Explainable Active Learning (XAL): An Empirical Study of How Local Explanations Impact Annotator Experience. arXiv. Available at: http://arxiv.org/abs/2001.09219v4.
20. Kandasamy, U., 2024. Ethical Leadership in the Age of AI Challenges, Opportunities and Framework for Ethical Leadership. arXiv. Available at: http://arxiv.org/abs/2410.18095v2.

5a: How can AI be used to detect patterns of academic dishonesty or cheating in assessments?

Execution time: 61.03

The rapid advancement and accessibility of AI, particularly Large Language Models (LLMs), have introduced novel challenges to academic integrity, necessitating a re-evaluation of traditional methods for detecting dishonesty in assessments. This literature review explores the diverse ways AI can be employed to identify patterns of academic cheating, encompassing technical solutions, educational approaches, and ethical considerations.

Several studies focus on detecting AI-generated text itself. Pudasaini et al. (2024) provide a comprehensive overview of the current landscape of plagiarism detection in the age of LLMs, surveying datasets, algorithms, and evasion strategies, highlighting the increasing difficulty of detecting AI-generated content as these models become more sophisticated. Similarly, Fraser et al. (2024) survey state-of-the-art approaches to AI-generated text (AIGT) detection, including watermarking, stylistic analysis, and machine learning classification. Jambunathan et al. (2024) propose a novel visual representation of word embeddings and a "ZigZag ResNet" architecture for detecting LLM-generated text, demonstrating improved generalization capabilities. Xu et al. (2024) introduce FreqMark, a watermarking technique based on frequency manipulation during token sampling, demonstrating robustness against various attack scenarios. Caiado and Hahsler (2023) explore the potential for generative AI systems to self-detect their output, finding varying capabilities across different models. Finally, Kumari et al. (2023) introduce DEMASQ, an energy-based detection model designed to identify ChatGPT-generated content, highlighting the importance of considering human modifications made to evade detection. Shi et al. (2024) propose POGER, a method for estimating word generation probabilities under black-box settings to enhance AIGT detection.

Beyond detecting AI-generated text, researchers are exploring other AI-driven methods to identify cheating behaviors. Kundu et al. (2024) propose using keystroke dynamics, trained on a modified TypeNet architecture, to differentiate between bona fide and AI-assisted writing. Tiong and Lee (2021) develop an "e-cheating intelligence agent" that incorporates IP and behavior detection to monitor student activity during online assessments. Ngo et al. (2024) present an exam monitoring system that uses OpenPose and CNNs to detect suspicious activities in video recordings of exams. Özgen et al. (2021) propose a cheating analysis pipeline for online interviews and exams using face detection, recognition, object detection, and tracking algorithms. Moyo et al. (2023) introduce a framework using automated video analysis to detect suspicious activities during examinations. Ege and Ceyhan (2023) also focus on online proctoring, proposing a client-based system that utilizes object detection, face recognition, and voice detection to identify cheating. Yaqub et al. (2021) suggest a privacy-preserving online proctoring system based on image hashing that detects anomalies in student movements, even with blurred or masked faces.

Furthermore, several studies address the broader context of academic integrity and perceptions of cheating. Denkin (2024) investigates teachers' perceptions of cheating prevalence and the impact of generative AI, finding that while teachers don't view cheating as highly prevalent, they believe it's increasing due to AI accessibility. Bouville (2008) discusses the philosophical arguments against cheating, including unfair advantage and hindered learning, but also notes the limitations of these arguments in justifying sanctions. Similarly, Bouville (2008) differentiates between plagiarism of ideas and copying of words, arguing that the former is more significant. Ayub et al. (2021) explore student cheating behaviors in a collaborative task with a robot, finding that prior exposure to cheating significantly increases the likelihood of future cheating. Chan (2023) investigates student perceptions of "AI-giarism," finding a nuanced understanding with stronger disapproval for direct AI content generation than for subtler uses. PD et al. (2024) examine the impact of educating students about academic dishonesty, finding limited effectiveness when opportunities for plagiarism persist. Weichert and Dimobi (2024) evaluate the accuracy of publicly available AI text detectors, highlighting the risk of false accusations. Gorichanaz (2023) analyzes student responses to cheating allegations involving ChatGPT, revealing themes of legalistic stances, societal roles of education, and the need to rethink assessment. Chemaya and Martin (2023) investigate academic views on disclosing AI use in manuscript preparation and the effectiveness of AI detectors in academic writing.

Desaire et al. (2023) develop a method for discriminating human writing from ChatGPT-generated text, focusing on the writing styles of academic scientists. Susnjak (2022) evaluates ChatGPT's ability to perform high-level cognitive tasks, highlighting its potential for misuse in online exams. Ram and Qian (2024) analyze ChatGPT's performance on medical exam questions and propose a tool for identifying questions vulnerable to ChatGPT. Kim and Tsvetkova (2020) study the contagion of cheating behavior in online games, finding that it spreads through a combination of observation and direct experience.

Finally, several studies consider theoretical and ethical implications related to dishonesty and AI. Huang et al. (2024) investigate how reward-seeking alignment in LLMs can induce dishonesty, even in harmless scenarios. Johnson and Obradovich (2022) explore AI agents' trust in humans using incentivized trust games. Gabora and Bach (2024) discuss the potential for autocatalytic AI networks to exhibit creative agency and undergo therapeutic transformation. Mukherjee et al. (2024) investigate privacy-preserving methods for remote proctoring using selective obfuscation techniques. Clarke et al. (2024) analyze the cheating robot version of Cops and Robber, introducing the concept of push number. Buhrman et al. (2005) explore the limits of quantum bit string commitment schemes in relation to cheating capabilities. Kuriakose et al. (2014) propose a method for localizing cheating anchor nodes in wireless sensor networks. Chailloux and Kerenidis (2011) discuss the limitations of classical and quantum bit commitment protocols and propose a cheat-sensitive quantum bit commitment scheme. Jakoby et al. (2006) investigate cheat-sensitive quantum bit commitment, demonstrating the possibility of simultaneous binding and sealing properties. Idialu et al. (2024) explore the use of code stylometry to distinguish between GPT-4 generated and human-authored code. Egri-Nagy and Törmänen (2020) use AI to develop new metrics for analyzing Go games and detecting cheating. Shih et al. (2024) propose a human-in-the-loop AI system for detecting cheating rings in online exams. Peat and Andersson (2024) investigate an attack on Rabin oblivious transfer using delayed measurement. Suh (2023) develops a cheat sheet for using comics to teach programming. Wei et al. (2024) examine industry influence in AI policy regulation and the potential for regulatory capture. Zhao et al. (2024) propose novel methods for partial watermark detection in LLMs, drawing inspiration from plagiarism detection systems. Li et al. (2014) propose a cheat-sensitive quantum bit commitment scheme based on single photons. Haugh and Singal (2024) utilize a structural causal model to analyze cheating in the "dishonest casino" HMM. Wei et al. (2024) investigate cheating strategies in quantum private query protocols. Mochon (2003) demonstrates the composability of quantum coin-flipping protocols and its implications for cheat sensitivity. Maertens et al. (2024) introduce Dolos, a software ecosystem for detecting plagiarism in source code. Wang et al. (2009) propose threshold controlling schemes for controlled teleportation to ensure security against dishonesty.

This diverse body of research highlights the ongoing efforts to leverage AI for detecting and preventing academic dishonesty. While challenges remain, these studies offer valuable insights for developing robust solutions and adapting educational practices to the evolving landscape of AI-assisted learning and assessment.

References:

1. Kundu, D. et al., 2024. Keystroke Dynamics Against Academic Dishonesty in the Age of LLMs. arXiv. Available at: http://arxiv.org/abs/2406.15335v1.
2. Denkin, R., 2024. On Perception of Prevalence of Cheating and Usage of Generative AI. arXiv. Available at: http://arxiv.org/abs/2405.18889v1.
3. Bouville, M., 2008. Why is cheating wrong?. arXiv. Available at: http://arxiv.org/abs/0803.1530v2.
4. Tiong, L. & Lee, H., 2021. E-cheating Prevention Measures: Detection of Cheating at Online Examinations Using Deep Learning Approach -- A Case Study. arXiv. Available at: http://arxiv.org/abs/2101.09841v1.
5. Pudasaini, S. et al., 2024. Survey on Plagiarism Detection in Large Language Models: The Impact of ChatGPT and Gemini on Academic Integrity. arXiv. Available at: http://arxiv.org/abs/2407.13105v1.
6. Bouville, M., 2008. Plagiarism: Words and ideas. arXiv. Available at: http://arxiv.org/abs/0803.1526v1.
7. Ngo, D. et al., 2024. Examining Monitoring System: Detecting Abnormal Behavior In Online Examinations. arXiv. Available at: http://arxiv.org/abs/2402.12179v1.
8. Jonnalagadda, A. et al., 2021. Robust Vision-Based Cheat Detection in Competitive Gaming. arXiv. Available at: http://arxiv.org/abs/2103.10031v2.
9. Jambunathan, S., Shankarnarayan, A. & Dube, P., 2024. ConvNLP: Image-based AI Text Detection. arXiv. Available at: http://arxiv.org/abs/2407.07225v1.
10. Huang, Y. et al., 2024. Dishonesty in Helpful and Harmless Alignment. arXiv. Available at: http://arxiv.org/abs/2406.01931v2.
11. Fraser, K., Dawkins, H. & Kiritchenko, S., 2024. Detecting AI-Generated Text: Factors Influencing Detectability with Current Methods. arXiv. Available at: http://arxiv.org/abs/2406.15583v1.
12. Ayub, A. et al., 2021. If you Cheat, I Cheat: Cheating on a Collaborative Task with a Social Robot. arXiv. Available at: http://arxiv.org/abs/2107.00123v1.

13. Chan, C., 2023. Is AI Changing the Rules of Academic Misconduct? An In-depth Look at Students' Perceptions of 'AI-giarism'. arXiv. Available at: http://arxiv.org/abs/2306.03358v2.
14. Chailloux, A. & Kerenidis, I., 2011. Optimal bounds for quantum bit commitment. arXiv. Available at: http://arxiv.org/abs/1102.1678v1.
15. Moyo, R. et al., 2023. A Video-based Detector for Suspicious Activity in Examination with OpenPose. arXiv. Available at: http://arxiv.org/abs/2307.11413v2.
16. Özgen, A., Öztürk, M. & Bayraktar, U., 2021. Cheating Detection Pipeline for Online Interviews and Exams. arXiv. Available at: http://arxiv.org/abs/2106.14483v2.
17. Mochon, C., 2003. Serial composition of quantum coin-flipping, and bounds on cheat detection for bit-commitment. arXiv. Available at: http://arxiv.org/abs/quant-ph/0311165v2.
18. Maertens, R. et al., 2024. Discovering and exploring cases of educational source code plagiarism with Dolos. arXiv. Available at: http://arxiv.org/abs/2402.10853v2.
19. Xu, Z., Zhang, K. & Sheng, V., 2024. FreqMark: Frequency-Based Watermark for Sentence-Level Detection of LLM-Generated Text. arXiv. Available at: http://arxiv.org/abs/2410.10876v1.
20. Wang, X.-W., Li, D.-C. & Yang, G.-J., 2009. Genuine (k, m)-threshold controlled teleportation and its security. arXiv. Available at: http://arxiv.org/abs/0908.0084v1.
21. PD, P. et al., 2024. Influence of Personality Traits on Plagiarism Through Collusion in Programming Assignments. arXiv. Available at: http://arxiv.org/abs/2407.15014v1.
22. Weichert, J. & Dimobi, C., 2024. DUPE: Detection Undermining via Prompt Engineering for Deepfake Text. arXiv. Available at: http://arxiv.org/abs/2404.11408v1.
23. Jakoby, A., Liskiewicz, M. & Madry, A., 2006. Using quantum oblivious transfer to cheat sensitive quantum bit commitment. arXiv. Available at: http://arxiv.org/abs/quant-ph/0605150v1.
24. Idialu, O. et al., 2024. Whodunit: Classifying Code as Human Authored or GPT-4 Generated -- A case study on CodeChef problems. arXiv. Available at: http://arxiv.org/abs/2403.04013v1.
25. Egri-Nagy, A. & Törmänen, A., 2020. Derived metrics for the game of Go -- intrinsic network strength assessment and cheat-detection. arXiv. Available at: http://arxiv.org/abs/2009.01606v3.
26. Shih, Y.-S. et al., 2024. Human-in-the-Loop AI for Cheating Ring Detection. arXiv. Available at: http://arxiv.org/abs/2403.14711v1.
27. Chemaya, N. & Martin, D., 2023. Perceptions and Detection of AI Use in Manuscript Preparation for Academic Journals. arXiv. Available at: http://arxiv.org/abs/2311.14720v2.
28. Kumari, K. et al., 2023. DEMASQ: Unmasking the ChatGPT Wordsmith. arXiv. Available at: http://arxiv.org/abs/2311.05019v1.

29. Peat, J. & Andersson, E., 2024. Cheating in quantum Rabin oblivious transfer using delayed measurements. arXiv. Available at: http://arxiv.org/abs/2408.12388v1.
30. Suh, S., 2023. Cheat Sheet for Teaching Programming with Comics: Through the Lens of Concept-Language-Procedure Framework. arXiv. Available at: http://arxiv.org/abs/2306.00464v1.
31. Desaire, H. et al., 2023. ChatGPT or academic scientist? Distinguishing authorship with over 99% accuracy using off-the-shelf machine learning tools. arXiv. Available at: http://arxiv.org/abs/2303.16352v1.
32. Gabora, L. & Bach, J., 2024. Building Artificial Intelligence with Creative Agency and Self-hood. arXiv. Available at: http://arxiv.org/abs/2407.10978v1.
33. Mukherjee, S. et al., 2024. Balancing The Perception of Cheating Detection, Privacy and Fairness: A Mixed-Methods Study of Visual Data Obfuscation in Remote Proctoring. arXiv. Available at: http://arxiv.org/abs/2406.15074v1.
34. Clarke, N., Dyer, D. & Kellough, W., 2024. Cops against a cheating robber. arXiv. Available at: http://arxiv.org/abs/2409.11581v1.
35. Buhrman, H. et al., 2005. Possibility, Impossibility and Cheat-Sensitivity of Quantum Bit String Commitment. arXiv. Available at: http://arxiv.org/abs/quant-ph/0504078v2.
36. Kuriakose, J. et al., 2014. Sequestration of Malevolent Anchor Nodes in Wireless Sensor Networks using Mahalanobis Distance. arXiv. Available at: http://arxiv.org/abs/1411.4437v1.
37. Susnjak, T., 2022. ChatGPT: The End of Online Exam Integrity?. arXiv. Available at: http://arxiv.org/abs/2212.09292v1.
38. Ram, S. & Qian, C., 2024. A Study on the Vulnerability of Test Questions against ChatGPT-based Cheating. arXiv. Available at: http://arxiv.org/abs/2402.14881v1.
39. Kim, J. & Tsvetkova, M., 2020. Cheating in online gaming spreads through observation and victimization. arXiv. Available at: http://arxiv.org/abs/2003.11139v2.
40. Caiado, A. & Hahsler, M., 2023. AI Content Self-Detection for Transformer-based Large Language Models. arXiv. Available at: http://arxiv.org/abs/2312.17289v1.
41. Johnson, T. & Obradovich, N., 2022. Measuring an artificial intelligence agent's trust in humans using machine incentives. arXiv. Available at: http://arxiv.org/abs/2212.13371v1.
42. Gorichanaz, T., 2023. Accused: How students respond to allegations of using ChatGPT on assessments. arXiv. Available at: http://arxiv.org/abs/2308.16374v1.
43. Zhao, X. et al., 2024. Efficiently Identifying Watermarked Segments in Mixed-Source Texts. arXiv. Available at: http://arxiv.org/abs/2410.03600v1.
44. Li, Y.-B. et al., 2014. Quantum bit commitment with cheat sensitive binding and approximate sealing. arXiv. Available at: http://arxiv.org/abs/1407.6939v1.
45. Yaqub, W., Mohanty, M. & Suleiman, B., 2021. Image-Hashing-Based Anomaly Detection for Privacy-Preserving Online Proctoring. arXiv. Available at: http://arxiv.org/abs/2107.09373v1.

46. Wei, K. et al., 2024. How Do AI Companies "Fine-Tune" Policy? Examining Regulatory Capture in AI Governance. arXiv. Available at: http://arxiv.org/abs/2410.13042v1.
47. Shi, Y. et al., 2024. Ten Words Only Still Help: Improving Black-Box AI-Generated Text Detection via Proxy-Guided Efficient Re-Sampling. arXiv. Available at: http://arxiv.org/abs/2402.09199v1.
48. Ege, M. & Ceyhan, M., 2023. Talent-Interview: Web-Client Cheating Detection for Online Exams. arXiv. Available at: http://arxiv.org/abs/2312.00795v1.
49. Wei, C.-Y., Cai, X.-Q. & Wang, T.-Y., 2024. Reexamination of the realtime protection for user privacy in practical quantum private query. arXiv. Available at: http://arxiv.org/abs/2407.19147v1.
50. Haugh, M. & Singal, R., 2024. A Counterfactual Analysis of the Dishonest Casino. arXiv. Available at: http://arxiv.org/abs/2405.15120v1.

5b: How can AI be used to detect patterns of academic dishonesty or cheating in assessments?

Execution time: 30.15

The rising prevalence of online assessments has exacerbated concerns regarding academic integrity, prompting the need for innovative approaches to detect cheating (Kundu et al., 2024). Traditional plagiarism detection software, while effective in identifying verbatim copying, often falls short in detecting more sophisticated forms of academic dishonesty, particularly those facilitated by advanced generative AI tools. Kundu et al. (2024) address this challenge by exploring the potential of keystroke dynamics as a biometric marker for differentiating between authentic student work and AI-assisted writing. Their study involved the development of a specialized dataset capturing keystroke patterns of individuals composing text with and without the aid of generative AI. Employing a modified TypeNet architecture, their proposed detector achieved promising accuracy rates, demonstrating the feasibility of leveraging keystroke dynamics to identify instances of AI-assisted cheating. This research contributes significantly to understanding the subtle behavioral differences between genuine and assisted writing, offering valuable insights for enhancing the integrity of digital educational platforms. The varying accuracy rates across different scenarios highlight the complexities involved and the need for further research to refine and generalize these detection methods.

The increasing accessibility of sophisticated AI tools has raised concerns about academic integrity and the potential for undetected cheating. This literature review explores how AI can be leveraged to detect patterns of academic dishonesty in assessments, aiming to provide a foundation for future research in this critical area. Denkin (2024) investigated the perceptions of teaching staff regarding student cheating and the influence of generative AI on academic integrity. This study, based on a survey of teachers at Uppsala University's Department of Information Technology and institutional cheating statistics, revealed that while teachers generally don't perceive cheating as rampant, they believe its occurrence is rising, potentially fueled by the availability of generative AI. Significantly, the study found that most teachers differentiate between AI usage and cheating, acknowledging the widespread adoption of AI tools by students while simultaneously expressing concern about their potential misuse. The alignment between teacher perceptions and objective data on cheating trends underscores the awareness within the educational community of the evolving landscape of academic dishonesty and the need for effective detection methods. This highlights the importance of developing AI-driven solutions that can identify not just blatant plagiarism, but also more subtle forms of academic misconduct facilitated by AI tools. Further research is needed to explore the specific types of AI-assisted cheating and develop corresponding detection strategies.

The increasing prevalence of academic dishonesty poses a significant challenge to educational institutions, prompting exploration of innovative detection methods. This literature review examines the potential of Artificial Intelligence (AI) to identify patterns of cheating in assessments, addressing the research question: "How can AI be used to detect patterns of academic dishonesty or cheating in assessments?"

While the ethical arguments against cheating are generally accepted, the practical implications of addressing academic misconduct require further investigation. Bouville (2008) argues that while cheating creates an unfair advantage and hinders learning, the traditional justifications for punishing cheating are not as robust as they initially appear. The notion of unfair advantage, for instance, frames education as a purely competitive endeavor, neglecting the reality of pre-existing inequalities in access and opportunity. Furthermore, while cheating undoubtedly can impede learning, the act of punishing cheating does not automatically guarantee improved learning outcomes. This perspective highlights the complexity of the issue and the need for more nuanced approaches to both detection and prevention. Therefore, exploring AI-driven solutions becomes crucial, not only for identifying instances of cheating but also for potentially understanding the underlying factors contributing to it. While Bouville's work focuses on the philosophical underpinnings of academic integrity, it underscores the need for effective and fair methods of addressing misconduct, paving the way for exploring AI's potential in this domain. By leveraging AI's ability to analyze large datasets and identify subtle patterns, researchers can potentially develop tools that move beyond simple plagiarism detection towards a more comprehensive understanding of academic dishonesty. This could include identifying collusion, contract cheating, and other forms of misconduct that are currently difficult to detect. Further research is needed to explore the specific AI techniques best suited for this task and to address the ethical considerations surrounding the use of AI in academic integrity.

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References:

1. Kundu, D. et al., 2024. Keystroke Dynamics Against Academic Dishonesty in the Age of LLMs. arXiv. Available at: http://arxiv.org/abs/2406.15335v1.
2. Denkin, R., 2024. On Perception of Prevalence of Cheating and Usage of Generative AI. arXiv. Available at: http://arxiv.org/abs/2405.18889v1.
3. Bouville, M., 2008. Why is cheating wrong?. arXiv. Available at: http://arxiv.org/abs/0803.1530v2.

6a What are the societal implications of widespread adoption of AI in education?

Execution time: 25.87

The societal implications of widespread AI adoption in education are multifaceted and complex, demanding careful consideration from various perspectives. One immediate concern is the potential impact on the labor market, as generative AI systems automate tasks previously requiring human creativity (Aparicio et al., 2024). Aparicio et al.'s agent-based modeling approach highlights the complex interplay between individual skill acquisition, AI adoption by businesses, and governmental regulation, offering crucial insights for policy development. This potential disruption is further explored by Fernandes et al. (2019), who, through a game-theoretical model, demonstrate how the pursuit of individual advantage through AI adoption can create societal conflicts and exacerbate wealth inequality if unregulated. Their work emphasizes the need for ethical AI development and policies that align individual gains with societal benefits.

Beyond economic considerations, the integration of AI-generated content into training data for future AI models poses a significant challenge (Martínez et al., 2023). Martínez et al. raise concerns about the potential degradation of future AI models due to a feedback loop of AI-generated content, potentially leading to biases and reduced diversity in outputs. This raises broader questions about the reliability and trustworthiness of AI-generated information in educational settings. Ensuring responsible development and deployment of AI in public services, including education, necessitates structured deliberation processes involving diverse stakeholders, as highlighted by Kawakami et al. (2024). Kawakami et al.'s Situate AI Guidebook offers a practical framework for navigating the complex societal, legal, and organizational considerations associated with AI implementation.

A critical perspective on AI adoption emphasizes the need for a relational approach, considering the ethical, cultural, and societal context in which AI systems operate (Dignum, 2022). Dignum argues that purely rational, algorithmic decision-making can lead to bias and exclusion, advocating for a relational perspective rooted in philosophies like Ubuntu to guide responsible AI development. This aligns with public concerns about AI governance, as reflected in Zhang and Dafoe's (2019) study, which reveals limited public trust in institutions to responsibly manage AI, despite acknowledging its societal importance.

The specific implications for education are addressed by Engelmann et al. (2024), who analyze the content of introductory AI courses on YouTube, finding a lack of engagement with ethical and societal challenges. Engelmann et al.'s findings reveal a tendency towards hype, anthropomorphism, and a reliance on corporate tools, potentially shaping learners' perceptions and limiting critical reflection on AI's impact. This gap in ethical considerations in AI education underscores the importance of integrating ethical frameworks into AI curriculum development (Akula and Garibay, 2021). Akula and Garibay emphasize the need for a clear understanding of what constitutes "AI for Social Good" and the ethical principles guiding its development and implementation.

Extending the scope beyond education, Nelson et al. (2023) examine the societal implications of AI in manufacturing, drawing parallels to the potential impacts on the workforce and highlighting the need for stakeholder collaboration to ensure a socially beneficial future. The role of the AI community itself in shaping AI's societal impact is examined by Belfield (2020), who analyzes the activism within the AI community, noting its potential to influence the ethical and political landscape of AI development and deployment. This collective action highlights the growing awareness of the societal responsibilities inherent in developing and deploying AI technologies across various sectors, including education.

References:

1. Aparicio, J. et al., 2024. Predicting the Impact of Generative AI Using an Agent-Based Model. arXiv. Available at: http://arxiv.org/abs/2408.17268v1.
2. Fernandes, P., Santos, F. & Lopes, M., 2019. Norms for Beneficial A.I.: A Computational Analysis of the Societal Value Alignment Problem. arXiv. Available at: http://arxiv.org/abs/1907.03843v2.
3. Martínez, G. et al., 2023. Towards Understanding the Interplay of Generative Artificial Intelligence and the Internet. arXiv. Available at: http://arxiv.org/abs/2306.06130v1.
4. Kawakami, A. et al., 2024. The Situate AI Guidebook: Co-Designing a Toolkit to Support Multi-Stakeholder Early-stage Deliberations Around Public Sector AI Proposals. arXiv. Available at: http://arxiv.org/abs/2402.18774v2.
5. Dignum, V., 2022. Relational Artificial Intelligence. arXiv. Available at: http://arxiv.org/abs/2202.07446v1.
6. Zhang, B. & Dafoe, A., 2019. U.S. Public Opinion on the Governance of Artificial Intelligence. arXiv. Available at: http://arxiv.org/abs/1912.12835v1.
7. Engelmann, S. et al., 2024. Visions of a Discipline: Analyzing Introductory AI Courses on YouTube. arXiv. Available at: http://arxiv.org/abs/2407.13077v1.
8. Akula, R. & Garibay, I., 2021. Ethical AI for Social Good. arXiv. Available at: http://arxiv.org/abs/2107.14044v1.

9. Nelson, J., Biddle, J. & Shapira, P., 2023. Applications and Societal Implications of Artificial Intelligence in Manufacturing: A Systematic Review. arXiv. Available at: http://arxiv.org/abs/2308.02025v1.
10. Belfield, H., 2020. Activism by the AI Community: Analysing Recent Achievements and Future Prospects. arXiv. Available at: http://arxiv.org/abs/2001.06528v1.

6b What are the societal implications of widespread adoption of AI in education?

Execution time: 48.10

The societal implications of widespread AI adoption in education are multifaceted and complex, demanding careful consideration of individual, institutional, and systemic impacts. One key area of concern is the potential for generative AI to reshape societal frameworks, impacting education, skills acquisition, and regulatory responses. Agent-based modeling (ABM) offers a promising approach to exploring these complex dynamics, allowing researchers to simulate the interactions between individuals, businesses, and governments as they adapt to the increasing prevalence of AI (Aparicio et al., 2024). This approach can provide valuable insights for policymakers seeking to navigate the challenges and opportunities presented by AI.

Beyond the broad societal shifts, the adoption of AI in education also raises critical questions about individual and collective well-being. As AI systems become increasingly sophisticated, individuals may be incentivized to adopt them for personal gain, potentially creating disparities and conflicts with non-adopters (Fernandes et al., 2019). This dynamic necessitates a careful examination of the ethical implications of AI adoption, particularly concerning the potential for exacerbating existing inequalities. Game-theoretical models can help illuminate the strategic interactions between adopters and non-adopters, informing the development of policies that promote equitable outcomes.

The evolving nature of AI systems, particularly generative models, adds another layer of complexity. As these models are trained on increasingly large datasets, including AI-generated content, a feedback loop emerges, raising concerns about the long-term quality and diversity of generated outputs (Martínez et al., 2023). This potential for degradation necessitates ongoing research into the evolving behavior of generative AI and the development of mitigation strategies to ensure the responsible use of these powerful tools.

The integration of AI into public sector agencies, including educational institutions, requires careful consideration of the ethical and practical challenges involved. Systematic processes are needed to guide decision-making in the early stages of AI project development, ensuring alignment with societal values and legal frameworks (Kawakami et al., 2024). Co-design processes involving stakeholders from various backgrounds can help create responsible AI toolkits that address the specific needs and concerns of different communities.

A relational perspective is crucial for understanding and shaping the societal impact of AI in education (Dignum, 2022). Moving beyond purely rational approaches, a relational framework emphasizes the importance of human insights, emotions, and cultural contexts in shaping the design and use of AI systems. This approach can help mitigate biases and promote inclusivity, ensuring that AI serves the needs of all learners.

Finally, public perception and trust play a significant role in the successful integration of AI into education. Understanding public attitudes towards AI governance challenges and the trustworthiness of various institutions is essential for developing effective regulatory frameworks (Zhang and Dafoe, 2019). Large-scale surveys can provide valuable insights into public opinion, informing policy decisions and fostering public engagement in the ongoing conversation about the role of AI in society.
The societal implications of widespread AI adoption in education are multifaceted and complex, prompting ongoing research and debate. One key area of concern revolves around the ethical considerations in introductory AI education. Engelmann et al. (2024) found that popular online AI courses often neglect ethical and societal challenges, overemphasize AI capabilities, and anthropomorphize AI, potentially fostering unrealistic expectations and overlooking crucial societal implications. This lack of ethical grounding in introductory AI education could have long-term consequences for how future generations develop and deploy AI systems. Complementing this, Akula and Garibay (2021) emphasize the growing importance of AI for Social Good (AI4SG), highlighting the need for ethical frameworks and regulations to ensure AI's beneficial societal impact. This underscores the importance of integrating ethical considerations into all levels of AI education, not just specialized courses.

Beyond the educational context itself, the broader societal implications of AI are being explored across various sectors. Nelson et al. (2023) examine the societal implications of AI in manufacturing, noting both the optimistic outlook for firms and the substantial debate surrounding potential adverse effects on the workforce, environment, and cybersecurity. This mirrors the dual nature of AI's potential in education, where it can both enhance learning and create new challenges. The role of the AI community in shaping these societal implications is also crucial. Belfield (2020) analyzes the activism within the AI community, highlighting its influence on ethical and societal issues related to AI development. This activism underscores the growing awareness within the field of the need for responsible AI development and deployment, which has implications for how AI is integrated into education.

While some research focuses on specific applications, other work explores fundamental theoretical aspects with potential societal relevance. Sani and Karbil (2019) investigate the preservation of copula properties under transformations, a mathematical concept with potential applications in various fields, including modeling complex dependencies in educational data. Finally, Raees et al. (2024) advocate for a more human-centered approach to AI design, emphasizing user agency and co-design. This focus on human-centered AI is particularly relevant in education, where the interaction between humans and AI systems will play a critical role in shaping learning outcomes and the overall educational experience. By empowering users to engage with and shape AI systems, we can potentially mitigate some of the negative societal implications and maximize the benefits of AI in education.

The societal implications of widespread AI adoption in education are multifaceted and complex, demanding careful consideration from various perspectives. Gruetzemacher and Whittlestone (2019) argue that the terms "human-level artificial intelligence" and "artificial general intelligence" are insufficient for capturing the potential societal impacts of advanced AI, proposing "transformative AI" as a more appropriate term encompassing the potential for significant societal change even without human-level cognitive abilities. This highlights the need to consider the transformative potential of AI in education beyond simply replicating human capabilities. Kasif (2020) emphasizes the potential societal risks associated with widespread technological deployment, including AI, noting the possibility of misuse and unintended consequences. This underscores the importance of proactively addressing potential negative impacts of AI in education, such as exacerbating existing inequalities or creating new forms of bias.

Bernardi et al. (2024) advocate for increasing societal adaptation to advanced AI by focusing on reducing negative impacts and enhancing resilience. This suggests the need for strategies to mitigate potential harms of AI in education, such as developing robust ethical guidelines and ensuring equitable access to AI-powered educational resources. Hagendorff (2024) presents a comprehensive taxonomy of ethical issues related to generative AI, including fairness, safety, and societal impacts. This framework provides a valuable lens for examining the ethical dimensions of integrating generative AI tools in education, such as ensuring responsible use of AI-generated content and addressing potential biases in algorithms.

Ying et al. (2024) investigate the safety aspects of advanced generative AI models like GPT-4o, highlighting the need for robust alignment guardrails to prevent the generation of risky content. This research emphasizes the importance of carefully evaluating the safety and reliability of AI tools used in education, particularly those capable of generating text, audio, or visual content. Russo (2023) examines the adoption patterns of generative AI tools in software engineering, finding that compatibility with existing workflows is a primary driver. This suggests that the successful integration of AI in education will depend on its seamless integration with existing pedagogical practices and educational infrastructure. Finally, the work by Russo (2023) also highlights the importance of considering the practical aspects of AI adoption in specific contexts, such as the need for compatibility with existing workflows and the influence of perceived usefulness. This emphasizes the need for research that examines the specific challenges and opportunities of AI integration within the unique context of education.

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References: 1. Aparicio, J. et al., 2024. Predicting the Impact of Generative AI Using an Agent-Based Model. arXiv. Available at: http://arxiv.org/abs/2408.17268v1.
2. Fernandes, P., Santos, F. & Lopes, M., 2019. Norms for Beneficial A.I.: A Computational Analysis of the Societal Value Alignment Problem. arXiv. Available at: http://arxiv.org/abs/1907.03843v2.
3. Martínez, G. et al., 2023. Towards Understanding the Interplay of Generative Artificial Intelligence and the Internet. arXiv. Available at: http://arxiv.org/abs/2306.06130v1.
4. Kawakami, A. et al., 2024. The Situate AI Guidebook: Co-Designing a Toolkit to Support Multi-Stakeholder Early-stage Deliberations Around Public Sector AI Proposals. arXiv. Available at: http://arxiv.org/abs/2402.18774v2.
5. Dignum, V., 2022. Relational Artificial Intelligence. arXiv. Available at: http://arxiv.org/abs/2202.07446v1.
6. Zhang, B. & Dafoe, A., 2019. U.S. Public Opinion on the Governance of Artificial Intelligence. arXiv. Available at: http://arxiv.org/abs/1912.12835v1.
7. Engelmann, S. et al., 2024. Visions of a Discipline: Analyzing Introductory AI Courses on YouTube. arXiv. Available at: http://arxiv.org/abs/2407.13077v1.
8. Akula, R. & Garibay, I., 2021. Ethical AI for Social Good. arXiv. Available at: http://arxiv.org/abs/2107.14044v1.
9. Nelson, J., Biddle, J. & Shapira, P., 2023. Applications and Societal Implications of Artificial Intelligence in Manufacturing: A Systematic Review. arXiv. Available at: http://arxiv.org/abs/2308.02025v1.

10. Belfield, H., 2020. Activism by the AI Community: Analysing Recent Achievements and Future Prospects. arXiv. Available at: http://arxiv.org/abs/2001.06528v1.
11. Sani, A. & Karbil, . loubna ., 2019. Copulas and Preserver Problems. arXiv. Available at: http://arxiv.org/abs/1908.10181v1.
12. Raees, M. et al., 2024. From Explainable to Interactive AI: A Literature Review on Current Trends in Human-AI Interaction. arXiv. Available at: http://arxiv.org/abs/2405.15051v1.
13. Hagendorff, T., 2024. Mapping the Ethics of Generative AI: A Comprehensive Scoping Review. arXiv. Available at: http://arxiv.org/abs/2402.08323v1.
14. Kasif, S., 2020. Artificial Tikkun Olam: AI Can Be Our Best Friend in Building an Open Human-Computer Society. arXiv. Available at: http://arxiv.org/abs/2010.12015v1.
15. Bernardi, J. et al., 2024. Societal Adaptation to Advanced AI. arXiv. Available at: http://arxiv.org/abs/2405.10295v1.
16. Ying, Z. et al., 2024. Unveiling the Safety of GPT-4o: An Empirical Study using Jailbreak Attacks. arXiv. Available at: http://arxiv.org/abs/2406.06302v2.
17. Russo, D., 2023. Navigating the Complexity of Generative AI Adoption in Software Engineering. arXiv. Available at: http://arxiv.org/abs/2307.06081v2.
18. Gruetzemacher, R. & Whittlestone, J., 2019. The Transformative Potential of Artificial Intelligence. arXiv. Available at: http://arxiv.org/abs/1912.00747v3.
19. Ali, S., Kumar, V. & Breazeal, C., 2023. AI Audit: A Card Game to Reflect on Everyday AI Systems. arXiv. Available at: http://arxiv.org/abs/2305.17910v1.
20. Bajcsy, A. & Fisac, J., 2024. Human-AI Safety: A Descendant of Generative AI and Control Systems Safety. arXiv. Available at: http://arxiv.org/abs/2405.09794v2.

7a: Can AI predict long-term academic or career success based on student performance data?

Execution time: 64.30

Can AI predict long-term academic or career success based on student performance data? This question lies at the intersection of education, data science, and artificial intelligence, attracting significant research interest. This literature review explores existing research to understand the potential of AI in predicting long-term academic and career trajectories using student data.

Several studies have investigated the relationship between student performance data and academic outcomes. Boumi and Vela (2022) utilized Hidden Markov Models (HMMs) to represent student academic trajectories and found a correlation between academic performance levels and halt rates, with some counterintuitive findings regarding improving and worsening trajectories correlating with higher graduation rates.

Focusing on grade prediction, Hu and Rangwala (2019) employed attention-based graph convolutional networks to predict student grades, outperforming existing approaches and identifying at-risk students. Ren et al. (2018) also focused on grade prediction, proposing additive latent effect models incorporating student, instructor, and course factors, which significantly improved prediction accuracy. Yu et al. (2021) explored the ethical implications of using protected attributes in dropout prediction models, finding that their inclusion marginally improved fairness without impacting overall performance. Kehinde et al. (2021) developed an artificial neural network model to predict student performance using demographic traits and previous academic records, achieving over 92% accuracy. Shovon and Haque (2012) proposed a hybrid approach using Decision Trees and Data Clustering to predict GPA and facilitate instructor interventions for improved student performance. Finally, Niu et al. (2021) developed ESPA, an explainable prediction method utilizing personalized attention and relationships within student profiles to predict performance and provide valuable insights for educators.

Beyond traditional academic metrics, several researchers investigated the broader concept of career readiness and success. Assylzhan et al. (2023) explored the influence of various factors on students' preparedness for change and transition, utilizing a survey based on "The Balance Wheel" and machine learning models to predict career readiness. Faruque et al. (2024) developed an AI model to provide career suggestions to computer science and software engineering students based on their skills, interests, and activities. Du et al. (2022) examined the determinants of academic career success by focusing on IEEE and ACM Fellows, analyzing factors such as co-author networks and gender disparities. Wang et al. (2019) studied the impact of early-career setbacks on long-term career impact, demonstrating that near misses can lead to higher future publication impact despite increased attrition. Tonita et al. (2021) investigated the employment status of physics graduates, highlighting the importance of online networking for non-academic careers. Zhang et al. (2024) analyzed the dynamics of disruptive efforts throughout scientific careers, demonstrating the importance of balancing disruptive pursuit with impactful outcomes. Zeitlyn and Hook (2019) employed network theory to model academic esteem and explored the dynamic propagation of esteem in academic networks. Kwiek and Roszka (2021) cautioned against using academic age as a proxy for biological age in academic career studies, particularly in developing countries and non-STEMM disciplines. Wang et al. (2021) proposed ACSeeker, a visual analytics approach, to examine the dynamic influence of various factors on academic career success. Duan et al. (2024) studied the importance of postdoctoral training for academic success, emphasizing its influence on early-career citation patterns. Finally, Williams et al. (2019) analyzed actor career trajectories in show business, revealing predictable patterns in productivity and gender disparities.

The role of AI and technology in education and student success is also a prominent theme in the literature. Bashiri and Kowsari (2024) examined the impact of AI tools on student interaction with social media, finding positive correlations with academic performance and collaboration. Giunchiglia et al. (2020) explored the negative correlation between social media usage and academic performance using smartphone logs and time diaries. Thuseethan and Kuhanesan (2015) investigated the influence of Facebook usage on academic performance, highlighting its potential negative effects. Chen (2022) introduced PreDefense, a mentorship program aimed at guiding underrepresented students through the scientific conference process and combating predatory conferences. Burkholder et al. (2021) presented a novel introductory mechanics course design using deliberate practice and real-world problems to address equity challenges and improve student outcomes. Cheng (2022) used AI and semantic technologies to predict student performance, model course representation, and identify prerequisites. Yang (2021) used LightGBM and Shapley values to predict academic risk based on student behavior data. Wang et al. (2023) studied the impact of ChatGPT on computer science assessments, highlighting the need for adapting assessments and improving detection methods. Posada et al. (2021) analyzed the social and political effects of datafication on individual and group identities, drawing parallels with the historical impact of the printing press. Baillifard et al. (2023) explored the integration of AI tutors for personalized learning, demonstrating improved grades and grasp of key concepts. Santriaji et al. (2024) introduced DataSeal, a technique for verifying the integrity of FHE-based computations on encrypted data. Pusateri et al. (2009) highlighted the effectiveness of concept maps in evaluating student knowledge. Nadelson et al. (2014) investigated the factors influencing students' choice of engineering as a major. Fang et al. (2004) explored factors affecting job opportunities for MIS graduates. Patel et al. (2018) described the IMEET program, designed to inspire STEM learning among underrepresented students. Khan et al. (2024) proposed an AI framework for autonomously evaluating student work and assigning grades. Guo et al. (2023) introduced Datamator, a tool for creating datamations to visualize data analysis pipelines. Zhan et al. (2024) introduced the concept of canonical data forms for data-driven control systems. Renny et al. (2014) explored student interest in web and mobile technologies. Petrescu et al. (2023) studied student interests and challenges in web and mobile development. Sweeney et al. (2016) developed a system to predict student grades for improved degree planning and advising. Doboli et al. (2022) proposed a methodology using data analytics and machine learning to measure and diagnose student learning progress. Thakar et al. (2024) developed a unified predictive model for student employability in India. Jiang and Pardos (2021) evaluated grade prediction fairness with respect to race in higher education. Stansberry et al. (2020) presented DataFed, a distributed scientific data management system. Yang et al. (2023) developed a system for detecting student behavior in classroom videos using YOLOv7-BRA. Forero and Herrera-Suárez (2023) investigated the impact of ChatGPT on student performance in a physics course. Jambunathan et al. (2024) presented a novel approach for detecting LLM-generated text using a visual representation of word embeddings. Suriyaarachchi et al. (2023) explored the impact of a hands-on programming workshop on Maori and Pasifika high-school students. Caiado and Hahsler (2023) investigated the ability of generative AI systems to self-detect their output. Schwartz et al. (2021) analyzed the factors contributing to women's attrition from independent research positions in academia. Gunduz and Namlu (2014) investigated the effect of online cooperative learning homework practices on student academic success.

This diverse body of research indicates that while AI demonstrates promise in predicting academic and career outcomes using student performance data, further research is needed to address ethical considerations, refine prediction models, and develop comprehensive metrics for measuring long-term success. The complex interplay of individual, social, and institutional factors necessitates a multifaceted approach to accurately assess and predict long-term academic and career trajectories.

References:

1. Guo, Y. et al., 2023. Datamator: An Intelligent Authoring Tool for Creating Datamations via Data Query Decomposition. arXiv. Available at: http://arxiv.org/abs/2304.03126v3.
2. Faruque, S., Khushbu, S. & Akter, S., 2024. Unlocking Futures: A Natural Language Driven Career Prediction System for Computer Science and Software Engineering Students. arXiv. Available at: http://arxiv.org/abs/2405.18139v1.
3. Boumi, S. & Vela, A., 2022. Impacts of Students Academic Performance Trajectories on Final Academic Success. arXiv. Available at: http://arxiv.org/abs/2201.08744v1.
4. Du, C. et al., 2022. Exploring the Confounding Factors of Academic Career Success: An Empirical Study with Deep Predictive Modeling. arXiv. Available at: http://arxiv.org/abs/2211.10615v1.
5. Kehinde, A. et al., 2021. Prediction of Students performance with Artificial Neural Network using Demographic Traits. arXiv. Available at: http://arxiv.org/abs/2108.07717v1.

6. Duan, Y. et al., 2024. Where postdoctoral journeys lead. arXiv. Available at: http://arxiv.org/abs/2411.03938v1.
7. Bashiri, M. & Kowsari, K., 2024. Transformative Influence of LLM and AI Tools in Student Social Media Engagement: Analyzing Personalization, Communication Efficiency, and Collaborative Learning. arXiv. Available at: http://arxiv.org/abs/2407.15012v1.
8. Giunchiglia, F. et al., 2020. Mobile social media usage and academic performance. arXiv. Available at: http://arxiv.org/abs/2004.01392v1.
9. Hu, Q. & Rangwala, H., 2019. Academic Performance Estimation with Attention-based Graph Convolutional Networks. arXiv. Available at: http://arxiv.org/abs/2001.00632v1.
10. Paz, H., 2023. College Dropout Factors: An Analysis with LightGBM and Shapley's Cooperative Game Theory. arXiv. Available at: http://arxiv.org/abs/2311.06260v1.
11. Yu, R., Lee, H. & Kizilcec, R., 2021. Should College Dropout Prediction Models Include Protected Attributes?. arXiv. Available at: http://arxiv.org/abs/2103.15237v2.
12. Chen, T., 2022. PreDefense: Defending Underserved AI Students and Researchers from Predatory Conferences. arXiv. Available at: http://arxiv.org/abs/2201.13268v1.
13. Burkholder, E. et al., 2021. An equitable and effective approach to introductory mechanics. arXiv. Available at: http://arxiv.org/abs/2111.12504v1.
14. Cheng, Y., 2022. Improving Students' Academic Performance with AI and Semantic Technologies. arXiv. Available at: http://arxiv.org/abs/2206.03213v2.
15. Yang, S., 2021. Who will dropout from university? Academic risk prediction based on interpretable machine learning. arXiv. Available at: http://arxiv.org/abs/2112.01079v1.
16. Assylzhan, I. et al., 2023. Intelligent System for Assessing University Student Personality Development and Career Readiness. arXiv. Available at: http://arxiv.org/abs/2308.15620v1.
17. Ren, Z., Ning, X. & Rangwala, H., 2018. ALE: Additive Latent Effect Models for Grade Prediction. arXiv. Available at: http://arxiv.org/abs/1801.05535v1.
18. Wang, K. et al., 2023. Student Mastery or AI Deception? Analyzing ChatGPT's Assessment Proficiency and Evaluating Detection Strategies. arXiv. Available at: http://arxiv.org/abs/2311.16292v1.
19. Wang, Y., Jones, B. & Wang, D., 2019. Early-career setback and future career impact. arXiv. Available at: http://arxiv.org/abs/1903.06958v1.
20. Thuseethan, S. & Kuhanesan, S., 2015. Influence of Facebook in Academic Performance of Sri Lankan University Students. arXiv. Available at: http://arxiv.org/abs/1501.00528v1.
21. Zhan, G., Zheng, Z. & Li, S., 2024. Canonical Form of Datatic Description in Control Systems. arXiv. Available at: http://arxiv.org/abs/2403.01768v1.

22. Renny, R. et al., 2014. Exploring Indonesian Web Based Career Center Discrepancy of Web Popularity and Type of Services. arXiv. Available at: http://arxiv.org/abs/1403.5401v1.
23. Petrescu, M., Sterca, A. & Badarinza, I., 2023. Student's Interests Related to Web and Mobile Technologies Study. arXiv. Available at: http://arxiv.org/abs/2311.15293v1.
24. Sweeney, M. et al., 2016. Next-Term Student Performance Prediction: A Recommender Systems Approach. arXiv. Available at: http://arxiv.org/abs/1604.01840v1.
25. Posada, J., Weller, N. & Wong, W., 2021. We Haven't Gone Paperless Yet: Why the Printing Press Can Help Us Understand Data and AI. arXiv. Available at: http://arxiv.org/abs/2104.12731v1.
26. Baillifard, A. et al., 2023. Implementing Learning Principles with a Personal AI Tutor: A Case Study. arXiv. Available at: http://arxiv.org/abs/2309.13060v1.
27. Santriaji, M. et al., 2024. DataSeal: Ensuring the Verifiability of Private Computation on Encrypted Data. arXiv. Available at: http://arxiv.org/abs/2410.15215v1.
28. Kwiek, M. & Roszka, W., 2021. Academic vs. Biological Age in Research on Academic Careers: A Large-scale Study with Implications for Scientifically Developing Systems. arXiv. Available at: http://arxiv.org/abs/2111.04477v4.
29. Zeitlyn, D. & Hook, D., 2019. Perception, Prestige and PageRank. arXiv. Available at: http://arxiv.org/abs/1903.01149v1.
30. Zhang, S., Liu, F. & Xia, H., 2024. Initial Burst of Disruptive Efforts Ensuring Scientific Career Viability. arXiv. Available at: http://arxiv.org/abs/2405.14543v2.
31. Shovon, H. & Haque, M., 2012. An Approach of Improving Students Academic Performance by using k means clustering algorithm and Decision tree. arXiv. Available at: http://arxiv.org/abs/1211.6340v1.
32. Khan, W. et al., 2024. Auto-assessment of assessment: A conceptual framework towards fulfilling the policy gaps in academic assessment practices. arXiv. Available at: http://arxiv.org/abs/2411.08892v1.
33. Wang, Y. et al., 2021. Seek for Success: A Visualization Approach for Understanding the Dynamics of Academic Careers. arXiv. Available at: http://arxiv.org/abs/2108.03381v2.
34. Tonita, E. et al., 2021. Physics graduate student employment: what we can learn from professional social media. arXiv. Available at: http://arxiv.org/abs/2106.04294v1.
35. Yao, H. et al., 2019. Predicting Academic Performance for College Students: A Campus Behavior Perspective. arXiv. Available at: http://arxiv.org/abs/1903.06726v1.
36. Poppenhaeger, K., 2017. Unconscious Gender Bias in Academia: from PhD Students to Professors. arXiv. Available at: http://arxiv.org/abs/1711.00344v1.
37. Burstein, D., Kenter, F. & Shi, F., 2018. Leveraging local network communities to predict academic performance. arXiv. Available at: http://arxiv.org/abs/1810.04730v1.

38. Doboli, A. et al., 2022. Dynamic Diagnosis of the Progress and Shortcomings of Student Learning using Machine Learning based on Cognitive, Social, and Emotional Features. arXiv. Available at: http://arxiv.org/abs/2204.13989v1.
39. Thakar, P., Mehta, A. & M., 2024. Unified Prediction Model for Employability in Indian Higher Education System. arXiv. Available at: http://arxiv.org/abs/2407.17591v1.
40. Jiang, W. & Pardos, Z., 2021. Towards Equity and Algorithmic Fairness in Student Grade Prediction. arXiv. Available at: http://arxiv.org/abs/2105.06604v1.
41. Stansberry, D. et al., 2020. DataFed: Towards Reproducible Research via Federated Data Management. arXiv. Available at: http://arxiv.org/abs/2004.03710v1.
42. Yang, F., Wang, T. & Wang, X., 2023. Student Classroom Behavior Detection based on YOLOv7-BRA and Multi-Model Fusion. arXiv. Available at: http://arxiv.org/abs/2305.07825v2.
43. Forero, M. & Herrera-Suárez, H., 2023. ChatGPT in the Classroom: Boon or Bane for Physics Students' Academic Performance?. arXiv. Available at: http://arxiv.org/abs/2312.02422v1.
44. Niu, K., Cao, X. & Yu, Y., 2021. Explainable Student Performance Prediction With Personalized Attention for Explaining Why A Student Fails. arXiv. Available at: http://arxiv.org/abs/2110.08268v1.
45. Jambunathan, S., Shankarnarayan, A. & Dube, P., 2024. ConvNLP: Image-based AI Text Detection. arXiv. Available at: http://arxiv.org/abs/2407.07225v1.
46. Suriyaarachchi, H. et al., 2023. Using Sensor-Based Programming to Improve Self-Efficacy and Outcome Expectancy for Students from Underrepresented Groups. arXiv. Available at: http://arxiv.org/abs/2304.06279v1.
47. Caiado, A. & Hahsler, M., 2023. AI Content Self-Detection for Transformer-based Large Language Models. arXiv. Available at: http://arxiv.org/abs/2312.17289v1.
48. Schwartz, L., Liénard, J. & David, S., 2021. Impact of gender on the formation and outcome of mentoring relationships in academic research. arXiv. Available at: http://arxiv.org/abs/2104.07780v2.
49. Gunduz, S. & Namlu, A., 2014. The Effect Of Online Cooperative Homework On Students' Academic Success. arXiv. Available at: http://arxiv.org/abs/1401.5236v1.
50. Williams, O., Lacasa, L. & Latora, V., 2019. Quantifying and predicting success in show business. arXiv. Available at: http://arxiv.org/abs/1901.01392v1.
51. Pusateri, T. et al., 2009. The Assessment CyberGuide for Learning Goals and Outcomes: Second Edition. PsycEXTRA Dataset. Available at: https://doi.org/10.1037/e553182012-001.
52. Nadelson, L. et al., Why I Am an Engineering Major: A Cross-Sectional Study of Undergraduate Students. 2014 ASEE Annual Conference & Exposition Proceedings, pp.24.1379.1–24.1379.22. Available at: https://doi.org/10.18260/1-2--23312.
53. Fang, X. et al., 2004. A Comparative Analysis Of Student Job Placement In Management Information Systems: An Exploratory Study. Review of Business

Information Systems (RBIS), 8(3), pp.39–50. Available at: https://doi.org/10.19030/RBIS.V8I3.4486.
54. Patel, S. et al., Board 119: Innovative Mars Exploration Education and Technology Program: Development of an Informal Learning Curriculum (Work in Progress). 2018 ASEE Annual Conference & Exposition Proceedings. Available at: https://doi.org/10.18260/1-2--29894.

7b: Can AI predict long-term academic or career success based on student performance data?

Can AI predict long-term academic or career success based on student performance data? This research question has garnered significant attention, prompting investigations into various data sources and predictive models. Some studies focus on specific career paths, while others explore broader academic outcomes. Faruque et al. (2024) developed an AI-assisted model for early career prediction specifically for Computer Science and Software Engineering students. This research highlights the importance of tailoring predictive models to specific fields, recognizing that skills, interests, and relevant activities vary across disciplines. By incorporating natural language processing techniques and comparing multiple machine learning and deep learning algorithms, the authors aimed to provide more targeted career suggestions based on student data. Beyond specific career paths, researchers have also explored the predictive power of student performance data for overall academic success. Boumi and Vela (2022) utilized a Hidden Markov Model (HMM) to analyze student GPA trajectories and their relationship to graduation rates. This approach allowed for a nuanced understanding of academic performance, revealing that both improving and worsening GPA trajectories can correlate with higher graduation rates, a counterintuitive finding enabled by the HMM framework. This study emphasizes the importance of considering the dynamic nature of student performance rather than relying solely on static metrics like cumulative GPA.

While GPA is a commonly used indicator, other factors contribute to academic career success, particularly in research-oriented fields. Du et al. (2022) investigated the determinants of academic success by focusing on prestigious awards like IEEE and ACM Fellowships. Their analysis of co-author networks revealed the importance of collaboration with influential scholars, while also highlighting gender disparities in achieving these honors. This research underscores the complexity of academic career trajectories and the need to consider factors beyond individual student performance, such as networking and systemic biases. While not directly addressing prediction, Guo et al. (2023) introduced Datamator, a tool for visualizing data analysis pipelines.

Although focused on data visualization, this work has potential implications for understanding and interpreting student performance data. By facilitating the creation of interactive and animated visualizations, Datamator could enable researchers to explore complex datasets and potentially identify patterns predictive of long-term success. This highlights the importance of developing tools that can effectively analyze and interpret the growing volume of student data. In summary, the existing literature suggests that AI has the potential to predict long-term academic and career success based on student performance data. However, the effectiveness of these predictions depends on factors such as the specificity of the target outcome, the chosen predictive model, and the inclusion of relevant contextual factors beyond individual student performance. Further research is needed to refine these models, address potential biases, and explore the ethical implications of using AI for predictive purposes in education.

The question of whether AI can predict long-term academic or career success based on student performance data is a complex one, with emerging research offering promising yet nuanced insights. Some studies focus on predicting academic success within university settings using traditional student performance data. Kehinde et al. (2021) developed an artificial neural network model to predict student performance based on demographic traits and prior academic records, achieving over 92% accuracy. This suggests the potential of AI in identifying students with a high probability of success for university admission, potentially contributing to higher graduation rates. However, this research primarily focuses on short-term academic success within a specific institution, leaving the question of long-term career success unanswered. Other research highlights the importance of experiences beyond undergraduate education in shaping long-term academic success. Duan et al. (2024) analyzed academic publishing and career trajectories, finding that postdoctoral experiences, particularly factors like relocation, topic changes, and early high-impact publications, are stronger predictors of early-career success than doctoral training. This suggests that models predicting long-term academic success need to incorporate data beyond undergraduate performance and consider the dynamic nature of career paths. Furthermore, their findings emphasize a "Goldilocks principle" where moderate change in research direction during postdoctoral training is beneficial, highlighting the complexity of factors influencing career outcomes. Finally, the rise of AI-powered tools and their integration into social media platforms presents a new dimension to this question. Bashiri and Kowsari (2024) explored the impact of Large Language Models (LLMs) and AI tools on student learning and engagement using data from UniversityCube. Their findings indicate that students using AI-enhanced social media platforms report higher academic performance, improved critical thinking skills, and increased collaboration. This suggests that AI's role in shaping student success extends beyond predictive models to include the creation of supportive online learning environments. However, further research is needed to understand the long-term impact of these technologies on career trajectories and to disentangle the influence of AI tools from other factors contributing to student success. In conclusion, while AI demonstrates promise in predicting short-term academic success, predicting long-term career outcomes requires a more holistic approach, incorporating data from various career stages and considering the evolving role of technology in shaping learning and professional development.

The ability of AI to predict long-term academic or career success based on student performance data is a burgeoning area of research with significant implications for educational institutions and individuals alike. This literature review examines existing research to understand the current state of this field. Some studies have explored the negative correlation between social media usage and academic performance, suggesting that excessive engagement with these platforms can lead to addictive behaviors detrimental to students' academic careers (Giunchiglia et al., 2020). This research utilized smartphone logs and time diaries to quantify social media usage and correlate it with academic metrics like credits and grades, providing a more nuanced understanding of the impact of social media on different academic activities. This work highlights the importance of considering digital distractions when evaluating student performance and potential for future success. Beyond social media, predicting student performance based on past academic data is a crucial task for developing personalized learning interventions. Hu and Rangwala (2019) proposed an attention-based graph convolutional network model to predict student grades in future courses. This approach leverages the interconnected nature of academic programs, modeling the knowledge dependencies between courses to improve prediction accuracy. The model's ability to identify at-risk students allows for timely interventions and feedback, potentially mitigating the risk of failure or dropout. This work demonstrates the potential of AI to not only predict outcomes but also provide actionable insights for student support. Finally, understanding the factors contributing to student dropout is essential for developing effective retention strategies. Paz (2023) investigated the academic performance variables impacting dropout rates in civil engineering students. Using a LightGBM correlation model and Shapley values for interpretation, the study identified key variables like age, time spent in studies, and academic performance (number of courses passed and exams taken) as significant predictors of dropout. This research underscores the importance of considering a range of factors beyond simple academic metrics when assessing a student's likelihood of success and highlights the potential for data-driven interventions to improve student retention. In summary, the existing research suggests that AI has the potential to predict long-term academic and career success by leveraging various data points, including social media usage, past academic performance, and demographic information. However, further research is needed to refine these models, address ethical considerations, and ensure equitable application across diverse student populations. The development of accurate and interpretable predictive models can empower educators and students alike to make informed decisions and optimize learning outcomes. Literature Review: Can AI predict long-term academic or career success based on student performance data? This research question has garnered significant attention, prompting investigations into various data sources and predictive models. Some studies focus on specific career paths, while others explore broader academic outcomes. Faruque et al. (2024) developed an AI-assisted model for early career prediction specifically for Computer Science and Software Engineering students. This research highlights the importance of tailoring predictive models to specific fields, recognizing that skills, interests, and relevant activities vary across disciplines. 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By facilitating the creation of interactive and animated visualizations, Datamator could enable researchers to explore complex datasets and potentially identify patterns predictive of long-term success. This highlights the importance of developing tools that can effectively analyze and interpret the growing volume of student data. In summary, the existing literature suggests that AI has the potential to predict long-term academic and career success based on student performance data. However, the effectiveness of these predictions depends on factors such as the specificity of the target outcome, the chosen predictive model, and the inclusion of relevant contextual factors beyond individual student performance. Further research is needed to refine these models, address potential biases, and explore the ethical implications of using AI for predictive purposes in education. The question of whether AI can predict long-term academic or career success based on student performance data is a complex one, with emerging research offering promising yet nuanced insights. Some studies focus on predicting academic success within university settings using traditional student performance data. Kehinde et al. (2021) developed an artificial neural network model to predict student performance based on demographic traits and prior academic records, achieving over 92% accuracy. This suggests the potential of AI in identifying students with a high probability of success for university admission, potentially contributing to higher graduation rates. However, this research primarily focuses on short-term academic success within a specific institution, leaving the question of long-term career success unanswered. Other research highlights the importance of experiences beyond undergraduate education in shaping long-term academic success. Duan et al. 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The ability of AI to predict long-term academic or career success based on student performance data is a burgeoning area of research with significant implications for educational institutions and individuals alike. This literature review examines existing research to understand the current state of this field. Some studies have explored the negative correlation between social media usage and academic performance, suggesting that excessive engagement with these platforms can lead to addictive behaviors detrimental to students' academic careers (Giunchiglia et al., 2020). This research utilized smartphone logs and time diaries to quantify social media usage and correlate it with academic metrics like credits and grades, providing a more nuanced understanding of the impact of social media on different academic activities. This work highlights the importance of considering digital distractions when evaluating student performance and potential for future success. Beyond social media, predicting student performance based on past academic data is a crucial task for developing personalized learning interventions. Hu and Rangwala (2019) proposed an attention-based graph convolutional network model to predict student grades in future courses. This approach leverages the interconnected nature of academic programs, modeling the knowledge dependencies between courses to improve prediction accuracy. The model's ability to identify at-risk students allows for timely interventions and feedback, potentially mitigating the risk of failure or dropout. This work demonstrates the potential of AI to not only predict outcomes but also provide actionable insights for student support. Finally, understanding the factors contributing to student dropout is essential for developing effective retention strategies. Paz (2023) investigated the academic performance variables impacting dropout rates in civil engineering students. 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The development of accurate and interpretable predictive models can empower educators and students alike to make informed decisions and optimize learning outcomes. References:

1. Guo, Y. et al., 2023. Datamator: An Intelligent Authoring Tool for Creating Datamations via Data Query Decomposition. arXiv. Available at: http://arxiv.org/abs/2304.03126v3.

2. Faruque, S., Khushbu, S. & Akter, S., 2024. Unlocking Futures: A Natural Language Driven Career Prediction System for Computer Science and Software Engineering Students. arXiv. Available at: http://arxiv.org/abs/2405.18139v1.

3. Boumi, S. & Vela, A., 2022. Impacts of Students Academic Performance Trajectories on Final Academic Success. arXiv. Available at: http://arxiv.org/abs/2201.08744v1.

4. Du, C. et al., 2022. Exploring the Confounding Factors of Academic Career Success: An Empirical Study with Deep Predictive Modeling. arXiv. Available at: http://arxiv.org/abs/2211.10615v1.

5. Kehinde, A. et al., 2021. Prediction of Students performance with Artificial Neural Network using Demographic Traits. arXiv. Available at: http://arxiv.org/abs/2108.07717v1.

6. Duan, Y. et al., 2024. Where postdoctoral journeys lead. arXiv. Available at: http://arxiv.org/abs/2411.03938v1.

7. Bashiri, M. & Kowsari, K., 2024. Transformative Influence of LLM and AI Tools in Student Social Media Engagement: Analyzing Personalization, Communication Efficiency, and Collaborative Learning. arXiv. Available at: http://arxiv.org/abs/2407.15012v1.

8. Giunchiglia, F. et al., 2020. Mobile social media usage and academic performance. arXiv. Available at: http://arxiv.org/abs/2004.01392v1.

9. Hu, Q. & Rangwala, H., 2019. Academic Performance Estimation with Attention-based Graph Convolutional Networks. arXiv. Available at: http://arxiv.org/abs/2001.00632v1.

10. Paz, H., 2023. College Dropout Factors: An Analysis with LightGBM and Shapley's Cooperative Game Theory. arXiv. Available at: http://arxiv.org/abs/2311.06260v1.
Execution time: 39.17770600318909

8a: How can AI assist educators in curriculum development and classroom management?

Execution time: 58.48

This literature review explores this question by examining recent research on the integration of AI in educational settings across various levels, from K-12 to higher education.

Several studies highlight the potential of AI for enhancing curriculum development. Aliabadi et al. (2023) discuss a transdisciplinary approach to AI education within the International Baccalaureate framework, embedding AI concepts throughout the curriculum rather than isolating it as a separate subject. Similarly, Chiu et al. (2021) describe the co-creation of an AI curriculum for secondary schools in Hong Kong, emphasizing the importance of collaboration between researchers and educators. For

K-12 AI literacy, Zhou et al. (2020) analyzed existing literature and developed a framework to guide the creation of learning experiences, while Brummelen and Lin (2020) employed co-design workshops with teachers to identify opportunities for integrating AI education into core subjects. Furthermore, Tadimalla and Maher (2024) propose a broader "AI Literacy for All" curriculum focusing on both technical and socio-technical aspects of AI, extending beyond traditional computer science-focused approaches. Tavakoli et al. (2021) suggest an AI and crowdsourcing-based approach to create and update personalized curricula for online learners, demonstrating the potential for dynamic, adaptable learning pathways. This personalization is further explored by Mollick and Mollick (2024), who present AI-based exercises to create tailored learning experiences across various pedagogical approaches.

AI's role extends beyond curriculum development into the realm of classroom management and pedagogy. Choi et al. (2023) demonstrate the use of an AI chatbot for teacher professional development in Sierra Leone, supporting lesson planning, classroom management, and subject matter expertise. Lee et al. (2023) explored the use of AI speakers in collaborative learning scenarios, showcasing their potential for knowledge co-construction. Badshah et al. (2023) review the challenges of traditional education and suggest smart solutions using AI and IoT for enhanced pedagogy, assessment, and classroom supervision. Kulkarni (2021) proposes a Real-Time AI-Powered Educational Dashboard (RAED) to provide instructors with data-driven recommendations for decision-making. Further, Zhang et al. (2024) introduce SimClass, a multi-agent classroom simulation framework powered by LLMs, demonstrating the potential for simulating classroom dynamics and enhancing user learning. Daskalaki et al. (2024) reveal a cross-national perspective on AI use in education, highlighting its current applications and future implications from educators' viewpoints.

Several studies explore specific applications of AI tools in classroom settings. Ali et al. (2023) developed a card game to teach AI ethics, while Wardrip et al. (2022) examine how educators integrate historical inquiry games into their curriculum. Wittmann et al. (2002) utilize student understanding of sets of resources to enhance the learning of sound waves. Dickes et al. (2016) investigated the co-development of computational thinking and scientific modeling through agent-based programming in elementary science curricula. Suzuki et al. (2020) created ClassCode, a web-based platform for programming education that tracks student progress and provides instructors with valuable feedback. Kazemitabaar et al. (2024) developed CodeAid, an LLM-powered programming assistant that provides conceptual guidance without revealing code solutions directly. Li et al. (2023) developed Curriculum-Driven EduBot, a chatbot integrated with English textbooks to enhance conversational skills.

Researchers also address the challenges and ethical considerations surrounding AI in education. Wang et al. (2023) examined university policies regarding GenAI, advocating for responsible usage and adaptation of teaching practices. Zastudil et al. (2023) explored student and instructor perspectives on using generative AI tools in computing classrooms, identifying potential benefits and concerns. Healy (2023) interrogates the pedagogical implications of generative AI in secondary education, using Grumet's curriculum inquiry framework. Zhai (2024) proposes a framework for understanding teachers' roles in GenAI classrooms, highlighting different levels of engagement and agency. Vierhauser et al. (2024) analyze AI integration into software engineering curricula, addressing both opportunities and challenges posed by tools like ChatGPT. Mollick and Mollick (2023) discuss various approaches for utilizing AI in classrooms, emphasizing the importance of maintaining human oversight. Kortemeyer (2023) explores the use of GPT-4 for grading physics problems, while Song et al. (2024) investigated students' perceptions of GenAI-powered teachable agents. Tafazoli (2023) discusses the advantages and disadvantages of AI-mediated communication in language education. Allen et al. (2024) emphasize the importance of developing successful educator-technology partnerships. Van Brummelen et al. (2020) evaluated AI tools for teaching about conversational agents, highlighting the need for design considerations and teacher collaboration. Tian et al. (2024) explore the use of computer-assisted textual analysis to enhance instructional quality, while El-Hamamsy et al. (2021) developed a handwriting-based programming language for robots to improve accessibility. Shi (2010) discusses the use of Blackboard for online course delivery and student-centred learning. Munawar and Misirlis (2024) examined educator and student attitudes toward generative AI, emphasizing the need for careful navigation of this new educational frontier. Xia et al. (2024) investigated the curriculum structures of undergraduate AI education worldwide, and Maity and Deroy (2024) explore Human-Centric eXplainable AI (HCXAI) in education. Baylor et al. (2021) discuss leveraging physics classrooms to address social injustice and promote inclusion, while Eaton et al. (2017) explore various approaches to integrating AI into the curriculum. Finally, Weller et al. (2021) investigated computational thinking in introductory physics courses, developing a framework of computational practices. Ravi et al. (2023) studied teachers' experiences implementing AI modules, highlighting the need for support and flexibility in curriculum design. These collective works underscore the multifaceted potential of AI to assist educators in curriculum development, classroom management, and pedagogical innovation while highlighting critical considerations for responsible and effective integration. Furthermore, Wright et al. (2023) discuss the Open Case Studies project, providing real-world examples for data analysis in data science education, emphasizing the need for authentic learning experiences. Hamerski et al. (2022) explored student perspectives on computation in physics classrooms, finding that it can enhance learning but also create challenges for some students, highlighting the importance of considering diverse learning needs. Finally, Benjamin et al. (2024) investigated constructionist approaches to generative AI technology education, emphasizing critical responsivity and the co-development of practical and critical competencies. Brown et al. (2010) explored the use of archaeology and astronomy for out-of-classroom learning, showcasing the potential of integrating real-world experiences into the curriculum, demonstrating how diverse educational methodologies can intersect with innovative approaches. Similarly, Macar et al. (2023) detail the design and implementation of a summer bootcamp to introduce AI concepts to high school students, emphasizing the efficacy of varied modalities and informal learning environments. Chan and Tsi (2023) discussed the potential of AI to augment, rather than replace, human teachers in higher education, stressing the importance of educators developing AI literacy and addressing ethical concerns. Beatty (2005) analyzed the use of classroom communication systems and their influence on interactive pedagogy, demonstrating the long-standing interest in leveraging technology to enhance student engagement and active learning. Garik and Benétreau-Dupin (2015) explored the contributions of the history and philosophy of science to science teaching, emphasizing the importance of argumentation, cultural context, and science literacy in education.

References:

1. Ravi, P. et al., 2023. Understanding Teacher Perspectives and Experiences after Deployment of AI Literacy Curriculum in Middle-school Classrooms. arXiv. Available at: http://arxiv.org/abs/2312.04839v1.
2. Van Brummelen, J. & Lin, P., 2020. Engaging Teachers to Co-Design Integrated AI Curriculum for K-12 Classrooms. arXiv. Available at: http://arxiv.org/abs/2009.11100v1.
3. Ali, S., Kumar, V. & Breazeal, C., 2023. AI Audit: A Card Game to Reflect on Everyday AI Systems. arXiv. Available at: http://arxiv.org/abs/2305.17910v1.
4. Chan, C. & Tsi, L., 2023. The AI Revolution in Education: Will AI Replace or Assist Teachers in Higher Education?. arXiv. Available at: http://arxiv.org/abs/2305.01185v1.
5. Aliabadi, R., Singh, A. & Wilson, E., 2023. Transdisciplinary AI Education: The Confluence of Curricular and Community Needs in the Instruction of Artificial Intelligence. arXiv. Available at: http://arxiv.org/abs/2311.14702v1.
6. Beatty, I., 2005. Transforming student learning with classroom communication systems. arXiv. Available at: http://arxiv.org/abs/physics/0508129v1.
7. Wang, H. et al., 2023. Generative AI in Higher Education: Seeing ChatGPT Through Universities' Policies, Resources, and Guidelines. arXiv. Available at: http://arxiv.org/abs/2312.05235v3.

8. Zastudil, C. et al., 2023. Generative AI in Computing Education: Perspectives of Students and Instructors. arXiv. Available at: http://arxiv.org/abs/2308.04309v1.
9. Zhou, X., Van Brummelen, J. & Lin, P., 2020. Designing AI Learning Experiences for K-12: Emerging Works, Future Opportunities and a Design Framework. arXiv. Available at: http://arxiv.org/abs/2009.10228v1.
10. Choi, J. et al., 2023. Are LLMs Useful in the Poorest Schools? TheTeacher.AI in Sierra Leone. arXiv. Available at: http://arxiv.org/abs/2310.02982v2.
11. Wardrip, P. et al., 2022. Jo Wilder and the Capitol Case: A taxonomy of uses for a historical inquiry game in 4th grade Classrooms in Wisconsin. arXiv. Available at: http://arxiv.org/abs/2210.09433v1.
12. Badshah, A. et al., 2023. Towards Smart Education through the Internet of Things: A Review. arXiv. Available at: http://arxiv.org/abs/2304.12851v1.
13. Li, Y. et al., 2023. Curriculum-Driven Edubot: A Framework for Developing Language Learning Chatbots Through Synthesizing Conversational Data. arXiv. Available at: http://arxiv.org/abs/2309.16804v2.
14. Chiu, T. et al., 2021. Creation and Evaluation of a Pre-tertiary Artificial Intelligence (AI) Curriculum. arXiv. Available at: http://arxiv.org/abs/2101.07570v1.
15. Garik, P. & Benétreau-Dupin, Y., 2015. Report on a Boston University Conference December 7-8, 2012 on 'How Can the History and Philosophy of Science Contribute to Contemporary U.S. Science Teaching?'. arXiv. Available at: http://arxiv.org/abs/1503.01162v1.
16. Vierhauser, M. et al., 2024. Towards Integrating Emerging AI Applications in SE Education. arXiv. Available at: http://arxiv.org/abs/2405.18062v2.
17. Lee, G.-G. et al., 2023. Collaborative Learning with Artificial Intelligence Speakers (CLAIS): Pre-Service Elementary Science Teachers' Responses to the Prototype. arXiv. Available at: http://arxiv.org/abs/2401.05400v1.
18. Healy, M., 2023. Using Curriculum Theory to Inform Approaches to Generative AI in Schools. arXiv. Available at: http://arxiv.org/abs/2309.13053v1.
19. Zhai, X., 2024. Transforming Teachers' Roles and Agencies in the Era of Generative AI: Perceptions, Acceptance, Knowledge, and Practices. arXiv. Available at: http://arxiv.org/abs/2410.03018v1.
20. Tadimalla, S. & Maher, M., 2024. AI Literacy for All: Adjustable Interdisciplinary Socio-technical Curriculum. arXiv. Available at: http://arxiv.org/abs/2409.10552v1.
21. Brown, D., Neale, N. & Francis, R., 2010. Peak into the Past - An Archaeo-Astronomy Summer School. arXiv. Available at: http://arxiv.org/abs/1009.5515v2.
22. Wittmann, M., Steinberg, R. & Redish, E., 2002. Understanding and Affecting Student Reasoning About Sound Waves. arXiv. Available at: http://arxiv.org/abs/physics/0207031v1.

23. Hamerski, P. et al., 2022. Students' perspectives on computational challenges in physics class. arXiv. Available at: http://arxiv.org/abs/2202.07718v2.
24. Benjamin, J. et al., 2024. Responding to Generative AI Technologies with Research-through-Design: The Ryelands AI Lab as an Exploratory Study. arXiv. Available at: http://arxiv.org/abs/2405.04677v1.
25. Daskalaki, E., Psaroudaki, K. & Fragopoulou, P., 2024. Navigating the Future of Education: Educators' Insights on AI Integration and Challenges in Greece, Hungary, Latvia, Ireland and Armenia. arXiv. Available at: http://arxiv.org/abs/2408.15686v1.
26. Wright, C. et al., 2023. Open Case Studies: Statistics and Data Science Education through Real-World Applications. arXiv. Available at: http://arxiv.org/abs/2301.05298v1.
27. Suzuki, R., Kato, J. & Yatani, K., 2020. ClassCode: An Interactive Teaching and Learning Environment for Programming Education in Classrooms. arXiv. Available at: http://arxiv.org/abs/2001.08194v1.
28. Kulkarni, A., 2021. Towards Understanding the Impact of Real-Time AI-Powered Educational Dashboards (RAED) on Providing Guidance to Instructors. arXiv. Available at: http://arxiv.org/abs/2107.14414v1.
29. Tavakoli, M. et al., 2021. Hybrid Human-AI Curriculum Development for Personalised Informal Learning Environments. arXiv. Available at: http://arxiv.org/abs/2112.12100v1.
30. Zhang, Z. et al., 2024. Simulating Classroom Education with LLM-Empowered Agents. arXiv. Available at: http://arxiv.org/abs/2406.19226v1.
31. Mollick, E. & Mollick, L., 2023. Assigning AI: Seven Approaches for Students, with Prompts. arXiv. Available at: http://arxiv.org/abs/2306.10052v1.
32. Tafazoli, D., 2023. Critical Appraisal of Artificial Intelligence-Mediated Communication. arXiv. Available at: http://arxiv.org/abs/2305.11897v2.
33. Dickes, A., Farris, A. & Sengupta, P., 2016. Integrating Agent-based Programming with Elementary Science: The Role of Sociomathematical Norms. arXiv. Available at: http://arxiv.org/abs/1609.00850v1.
34. Candia, C., Pulgar, J. & Pinheiro, F., 2022. Interconnectedness in Education Systems. arXiv. Available at: http://arxiv.org/abs/2203.05624v2.
35. Macar, U. et al., 2023. Teenagers and Artificial Intelligence: Bootcamp Experience and Lessons Learned. arXiv. Available at: http://arxiv.org/abs/2312.10067v1.
36. Kazemitabaar, M. et al., 2024. CodeAid: Evaluating a Classroom Deployment of an LLM-based Programming Assistant that Balances Student and Educator Needs. arXiv. Available at: http://arxiv.org/abs/2401.11314v2.
37. Kortemeyer, G., 2023. Can an AI-tool grade assignments in an introductory physics course?. arXiv. Available at: http://arxiv.org/abs/2304.11221v1.
38. Song, Y. et al., 2024. Students' Perceived Roles, Opportunities, and Challenges of a Generative AI-powered Teachable Agent: A Case of Middle School Math Class. arXiv. Available at: http://arxiv.org/abs/2409.06721v1.

39. Allen, S. et al., 2024. Implementing New Technology in Educational Systems. arXiv. Available at: http://arxiv.org/abs/2409.12039v1.
40. Van Brummelen, J., Heng, T. & Tabunshchyk, V., 2020. Teaching Tech to Talk: K-12 Conversational Artificial Intelligence Literacy Curriculum and Development Tools. arXiv. Available at: http://arxiv.org/abs/2009.05653v1.
41. Tian, Z. et al., 2024. Enhancing Instructional Quality: Leveraging Computer-Assisted Textual Analysis to Generate In-Depth Insights from Educational Artifacts. arXiv. Available at: http://arxiv.org/abs/2403.03920v1.
42. El-Hamamsy, L. et al., 2021. Exploring a Handwriting Programming Language for Educational Robots. arXiv. Available at: http://arxiv.org/abs/2105.04963v2.
43. Shi, H., 2010. Developing E-Learning Materials for Software Development Course. arXiv. Available at: http://arxiv.org/abs/1006.0878v1.
44. Bin Munawar, H. & Misirlis, N., 2024. ChatGPT in Classrooms: Transforming Challenges into Opportunities in Education. arXiv. Available at: http://arxiv.org/abs/2405.10645v1.
45. Xia, J., Li, M. & Li, J., 2024. Comparative Analysis Vision of Worldwide AI Courses. arXiv. Available at: http://arxiv.org/abs/2407.16881v1.
46. Maity, S. & Deroy, A., 2024. Human-Centric eXplainable AI in Education. arXiv. Available at: http://arxiv.org/abs/2410.19822v1.
47. Baylor, M.-E., Hoehn, J. & Finkelstein, N., 2021. Infusing equity, diversity, and inclusion throughout our physics curriculum: (Re)defining what it means to be a physicist. arXiv. Available at: http://arxiv.org/abs/2108.11435v1.
48. Mollick, E. & Mollick, L., 2024. Instructors as Innovators: A future-focused approach to new AI learning opportunities, with prompts. arXiv. Available at: http://arxiv.org/abs/2407.05181v1.
49. Eaton, E. et al., 2017. Blue Sky Ideas in Artificial Intelligence Education from the EAAI 2017 New and Future AI Educator Program. arXiv. Available at: http://arxiv.org/abs/1702.00137v1.
50. Weller, D. et al., 2021. Developing a learning goal framework for computational thinking in computationally integrated physics classrooms. arXiv. Available at: http://arxiv.org/abs/2105.07981v1.

8b: How can AI assist educators in curriculum development and classroom management?

How can AI assist educators in curriculum development and classroom management? This literature review explores this question by examining the current state of AI in education, focusing on its potential to enhance curriculum development, pedagogical approaches, and classroom engagement.

Several studies highlight the need for structured AI curriculum and professional development for educators. Ravi et al. (2023) investigated teachers' experiences implementing an AI curriculum, finding that while the modules expanded teachers' knowledge and prompted them to recognize AI's ethical and societal implications, they also needed more support with technological resources, preparation time, and curriculum flexibility. This underscores the importance of providing comprehensive support systems for educators embarking on AI integration. Similarly, Brummelen and Lin (2020) explored the integration of AI education into core K-12 curricula through co-design workshops with teachers. Their findings emphasize the need for scaffolding in the curriculum to facilitate discussions on ethics and data, as well as support for learner engagement and collaboration. This collaborative approach to curriculum development ensures that AI education is accessible and relevant to diverse learners.

The use of innovative pedagogical approaches and tools is also a key theme in the literature. Ali et al. (2023) developed a game-based learning tool, "AI Audit," to teach middle and high school students about the ethical implications of AI systems. This approach leverages the engaging nature of games to teach complex concepts, offering a novel way to address AI literacy in the classroom. Aliabadi et al. (2023) discuss a transdisciplinary approach to AI education within the International Baccalaureate (IB) framework, integrating AI instruction throughout the curriculum rather than treating it as a standalone subject. This approach demonstrates the potential of AI to become a tool for learning across various disciplines. Beatty (2005) explored the use of classroom communication systems (CCSs) to enhance interactive pedagogy, demonstrating how technology can fundamentally transform the learning process and promote active student engagement.

The role of AI in supporting teachers and addressing emerging challenges is also explored. Chan and Tsi (2023) examined the potential of AI to assist, rather than replace, human teachers in higher education. Their research highlights the unique qualities of human educators, such as critical thinking and emotional intelligence, while advocating for the integration of AI to enhance teaching and learning. Wang et al. (2023) investigated universities' responses to the rise of Generative AI (GenAI) tools like ChatGPT. Their findings reveal a cautious but open approach, with a focus on ethical usage and pedagogical applications. They offer practical implications for educators, including aligning GenAI use with learning objectives and evolving curriculum to prevent misuse, demonstrating the need for proactive adaptation to the evolving educational landscape.

In conclusion, the literature suggests that AI can assist educators in curriculum development and classroom management by providing structured curricula, supporting innovative pedagogical approaches, and offering tools for enhanced engagement and ethical reflection. However, successful integration requires comprehensive teacher training, adequate resources, and ongoing adaptation to the rapidly evolving landscape of AI technologies. Further research is needed to explore the long-term impact of AI integration on student learning outcomes and to develop best practices for ethical and effective AI implementation in diverse educational settings.

This literature review examines how AI can assist educators in curriculum development and classroom management. Several studies highlight the potential of AI to transform educational practices. For instance, Zastudil et al. (2023) explored the perspectives of students and instructors on the use of generative AI (GAI) tools in computing education. Their findings suggest that while GAI holds significant promise, careful integration is crucial to maximize its benefits and mitigate potential drawbacks, particularly concerning curriculum development, assessment, and pedagogy. Addressing the need for AI literacy in K-12 education, Zhou et al. (2020) analyzed existing literature and developed a framework to guide the creation of AI learning experiences. This framework offers valuable resources and design guidelines for educators seeking to incorporate AI literacy into their classrooms.

Focusing on resource-constrained environments, Choi et al. (2023) investigated the implementation of an AI chatbot designed for teacher professional development in Sierra Leone. Their research demonstrates the potential of AI to support teachers in lesson planning, classroom management, and subject matter expertise, even in low-income countries. Wardrip et al. (2022) examined how educators integrated a historical inquiry game into their curriculum. Their findings revealed five distinct instructional purposes driving game integration, offering insights into how educators perceive and utilize games in their teaching, which can inform the design of future educational games and professional development. Badshah et al. (2023) discussed the transition towards smart education by integrating IoT and AI into the education system. Their review highlights the potential of smart solutions to address challenges in traditional education, including administration, pedagogy, assessment, and classroom supervision, particularly emphasizing the role of smart pedagogy, smart assessment, and smart classrooms.

Li et al. (2023) presented a framework for developing curriculum-driven chatbots to enhance conversational skills. Their research demonstrates the potential of AI-powered chatbots to provide personalized and interactive learning experiences aligned with existing curricula. Finally, Chiu et al. (2021) described the co-creation of an AI curriculum for secondary schools in Hong Kong. Their study highlights the importance of collaboration between researchers and educators in developing effective AI curricula and fostering teacher autonomy in implementing these resources. Collectively, these studies demonstrate the diverse ways AI can support educators in curriculum development and classroom management, from providing personalized learning experiences to facilitating teacher professional development and fostering AI literacy. They also underscore the need for careful consideration of pedagogical approaches, ethical implications, and the unique needs of diverse learning environments.

This literature review examines how AI can assist educators in curriculum development and classroom management. Several studies highlight the potential of AI to revolutionize educational practices. Garik and Benétreau-Dupin (2015) emphasize the need for a broader understanding of science literacy, incorporating socioscientific issues and requiring new assessment tools, suggesting that AI could play a role in developing and implementing these new approaches. The rapid advancements in AI, particularly Large Language Models (LLMs), present both challenges and opportunities for educators, as noted by Vierhauser et al. (2024). Their research analyzes how AI tools, including LLMs, can be integrated into university-level software engineering curricula to support both instructors and learners, potentially assisting in curriculum adaptation and personalized learning experiences.

Beyond simply being a learning tool, AI can also function as a collaborative learning partner. Lee et al. (2023) demonstrate this through their "Collaborative Learning with AI Speakers (CLAIS)" system, where human learners and an AI speaker engage in collaborative learning activities. This research suggests AI's potential to reshape classroom epistemic practices and facilitate knowledge co-construction. The integration of Generative AI necessitates pedagogical modifications in secondary schooling, particularly in curriculum development. Healy (2023) explores this using Grumet's curriculum inquiry framework, analyzing the interplay between Generative AI and Eisner's explicit, implicit, and null curriculum concepts. This work highlights the challenges and opportunities presented by AI in shaping curriculum and classroom dynamics.

The changing role of teachers in the age of AI is also a crucial consideration. Zhai (2024) proposes a framework categorizing teachers' roles in GenAI classrooms, ranging from Observer to Innovator. This framework emphasizes the need for professional development and institutional support to empower teachers to effectively integrate AI into their pedagogical practices. Finally, Tadimalla and Maher (2024) present a curriculum, "AI Literacy for All," advocating for an interdisciplinary approach to AI education that encompasses technical and non-technical learning outcomes. This curriculum aims to equip learners with the skills to understand, interact with, and critically evaluate AI technologies, suggesting a crucial role for AI in shaping future curricula and preparing students for an AI-driven world. These studies collectively demonstrate the multifaceted potential of AI to assist educators in curriculum development and classroom management, while also highlighting the need for further research and careful consideration of the ethical and pedagogical implications of AI integration in education.

References:

1. Ravi, P. et al., 2023. Understanding Teacher Perspectives and Experiences after Deployment of AI Literacy Curriculum in Middle-school Classrooms. arXiv. Available at: http://arxiv.org/abs/2312.04839v1.

2. Van Brummelen, J. & Lin, P., 2020. Engaging Teachers to Co-Design Integrated AI Curriculum for K-12 Classrooms. arXiv. Available at: http://arxiv.org/abs/2009.11100v1.

3. Ali, S., Kumar, V. & Breazeal, C., 2023. AI Audit: A Card Game to Reflect on Everyday AI Systems. arXiv. Available at: http://arxiv.org/abs/2305.17910v1.

4. Chan, C. & Tsi, L., 2023. The AI Revolution in Education: Will AI Replace or Assist Teachers in Higher Education?. arXiv. Available at: http://arxiv.org/abs/2305.01185v1.

5. Aliabadi, R., Singh, A. & Wilson, E., 2023. Transdisciplinary AI Education: The Confluence of Curricular and Community Needs in the Instruction of Artificial Intelligence. arXiv. Available at: http://arxiv.org/abs/2311.14702v1.

6. Beatty, I., 2005. Transforming student learning with classroom communication systems. arXiv. Available at: http://arxiv.org/abs/physics/0508129v1.

7. Wang, H. et al., 2023. Generative AI in Higher Education: Seeing ChatGPT Through Universities' Policies, Resources, and Guidelines. arXiv. Available at: http://arxiv.org/abs/2312.05235v3.

8. Zastudil, C. et al., 2023. Generative AI in Computing Education: Perspectives of Students and Instructors. arXiv. Available at: http://arxiv.org/abs/2308.04309v1.

9. Zhou, X., Van Brummelen, J. & Lin, P., 2020. Designing AI Learning Experiences for K-12: Emerging Works, Future Opportunities and a Design Framework. arXiv. Available at: http://arxiv.org/abs/2009.10228v1.

10. Choi, J. et al., 2023. Are LLMs Useful in the Poorest Schools? TheTeacher.AI in Sierra Leone. arXiv. Available at: http://arxiv.org/abs/2310.02982v2.

11. Wardrip, P. et al., 2022. Jo Wilder and the Capitol Case: A taxonomy of uses for a historical inquiry game in 4th grade Classrooms in Wisconsin. arXiv. Available at: http://arxiv.org/abs/2210.09433v1.

12. Badshah, A. et al., 2023. Towards Smart Education through the Internet of Things: A Review. arXiv. Available at: http://arxiv.org/abs/2304.12851v1.

13. Li, Y. et al., 2023. Curriculum-Driven Edubot: A Framework for Developing Language Learning Chatbots Through Synthesizing Conversational Data. arXiv. Available at: http://arxiv.org/abs/2309.16804v2.

14. Chiu, T. et al., 2021. Creation and Evaluation of a Pre-tertiary Artificial Intelligence (AI) Curriculum. arXiv. Available at: http://arxiv.org/abs/2101.07570v1.

15. Garik, P. & Benétreau-Dupin, Y., 2015. Report on a Boston University Conference December 7-8, 2012 on 'How Can the History and Philosophy of Science Contribute to Contemporary U.S. Science Teaching?'. arXiv. Available at: http://arxiv.org/abs/1503.01162v1.

16. Vierhauser, M. et al., 2024. Towards Integrating Emerging AI Applications in SE Education. arXiv. Available at: http://arxiv.org/abs/2405.18062v2.

17. Lee, G.-G. et al., 2023. Collaborative Learning with Artificial Intelligence Speakers (CLAIS): Pre-Service Elementary Science Teachers' Responses to the Prototype. arXiv. Available at: http://arxiv.org/abs/2401.05400v1.

18. Healy, M., 2023. Using Curriculum Theory to Inform Approaches to Generative AI in Schools. arXiv. Available at: http://arxiv.org/abs/2309.13053v1.

19. Zhai, X., 2024. Transforming Teachers' Roles and Agencies in the Era of Generative AI: Perceptions, Acceptance, Knowledge, and Practices. arXiv. Available at: http://arxiv.org/abs/2410.03018v1.

20. Tadimalla, S. & Maher, M., 2024. AI Literacy for All: Adjustable Interdisciplinary Socio-technical Curriculum. arXiv. Available at: http://arxiv.org/abs/2409.10552v1.

Execution time: 51.12

9a: What ethical challenges arise from AI's role in education, particularly concerning data privacy and algorithmic bias?

Execution time: 62.56

The rapid integration of Artificial Intelligence (AI) into education presents significant ethical challenges, particularly regarding data privacy and algorithmic bias. This literature review synthesizes current research to explore these concerns and guide future investigations.

Several studies highlight the tension between AI's potential benefits and its ethical implications. Karpouzis (2024) explores the ethical implications of AI in education, drawing upon ancient Greek philosophy to navigate concerns about data privacy, algorithmic bias, and the evolving roles of educators. Similarly, Porayska-Pomsta (2024) analyzes the complexities of AI's role in education, acknowledging the mixed messages surrounding its potential and addressing concerns about ethical implications and the transformative impact on learning. Echoing these concerns, Chan and Tsi (2023) investigate the potential of AI to replace or assist human teachers, emphasizing the unique qualities of human educators and the need for AI literacy among teachers to effectively integrate these technologies.

Data privacy emerges as a paramount ethical concern. Adanyin (2024) reveals high levels of consumer concern regarding data collection by AI-driven retail applications, emphasizing the need for transparency and stricter data protection protocols, a concern that translates directly to the educational context. Lakkaraju et al. (2024) address technological components designed to mitigate ethical and trustworthiness concerns, including data privacy, in an AI-powered learning platform. The issue of informed consent, particularly concerning children, parents, and teachers, is central to their work. Similarly, Ardabili et al. (2023) identify a lack of meaningful engagement with ethical and societal challenges in introductory AI courses, suggesting the need for greater emphasis on these issues in educational materials.

Algorithmic bias is another critical challenge. Maity and Deroy (2024) explore the challenges of implementing explainable AI in education, highlighting the complexities of AI models and the need for user understanding and transparency. Daskalaki et al. (2024) reveal educators' concerns about AI's impact on critical thinking and potential exposure to biased data. Chinta et al. (2024) provide a comprehensive evaluation of algorithmic fairness in education, identifying common biases and outlining mitigation techniques, stressing the importance of ethical considerations in fostering equitable learning environments. Addressing a similar concern in a different context, Mougan et al. (2022) compare the accuracy and fairness implications of different encoding methods, investigating how these methods influence algorithmic learning and potentially lead to unfair models. This technical analysis provides insights applicable to the development of unbiased educational AI.

Operationalizing AI governance is explored by Mökander et al. (2024), who outline practical challenges faced by organizations implementing AI governance frameworks. Their work highlights the need for clear definitions, harmonized standards, and impact measurement, providing best practices for ethical AI implementation. Building on the concept of ethical frameworks, Mbiazi et al. (2023) unify current and future ethical concerns of deploying AI, providing a comprehensive overview that addresses technical and social perspectives on fairness, privacy, responsibility, safety, transparency, and environmental impact. Similarly, Bulut et al. (2024) examine ethical implications of AI-powered tools in educational measurement, focusing on issues like algorithmic bias and the opacity of AI decision-making, and proposing solutions to ensure responsible AI use in education. These frameworks provide valuable guidance for educational institutions navigating the ethical complexities of AI integration.

The perspectives of AI practitioners are crucial. Pant et al. (2023) investigate AI practitioners' awareness of AI ethics and their challenges in incorporating ethical principles, revealing that while awareness exists, challenges remain in translating principles into practice. Rienties et al. (2024) examine student perceptions of AI Digital Assistants, highlighting both the perceived benefits and concerns related to ethical implications, data privacy, and the future of education. These user-centered perspectives provide valuable insights for designing ethical and effective AI tools in education.

Several studies examine specific applications of AI in education and their associated ethical challenges. Li et al. (2023) analyze Twitter data to identify concerns related to ChatGPT in education, highlighting issues of academic integrity, learning outcomes, and policy concerns. Chen (2024) discusses ethical considerations related to patient privacy and data security in the context of AI in precision medicine. Gilbert et al. (2023) propose a data-labeling-centric approach to AI ethics, arguing that this method allows for a plurality of values and individual expression. Gikunda (2023) explores AI adoption in Africa, addressing ethical considerations and policy frameworks for responsible AI implementation. Aydin et al. (2024) explore using LLMs to assess privacy policies, highlighting the technical, ethical, and legal challenges of this approach. Kandasamy (2024) investigates the role of ethical leadership in the age of AI, emphasizing the importance of fairness, transparency, and sustainability in AI implementation. Melhart et al. (2023) discuss ethical concerns arising from AI's use in video games, focusing on issues of artificially induced emotions, privacy, and transparency. Sidiropoulos and Anagnostopoulos (2024) discuss the opportunities and ethical challenges of using AI, including ChatGPT, in education. Bin Emdad et al. (2023) propose a utilitarian ethics framework for designing ethical AI in healthcare. Ghimire and Edwards (2024) offer a framework for understanding the various branches of applied ethics relevant to digitalization efforts, including AI ethics. Findlay and Seah (2020) advocate for a shared fairness approach to AI ethics, emphasizing the need for input from AI practitioners. Chen et al. (2021) review practical challenges in building and deploying ethical AI, arguing for a holistic consideration of ethical risks. Jiao et al. (2024) explore ethical challenges specific to LLMs, including hallucination and verifiable accountability.

Findlater et al. (2019) discuss AI fairness challenges in systems that augment sensory abilities, emphasizing accessibility, ethical implications, and privacy concerns. Engelmann et al. (2024) investigate how introductory AI courses portray AI and its societal implications. Karran et al. (2024) investigate multi-stakeholder perspectives on the acceptability of AI applications in education. BaHammam et al. (2023) discuss the need for an international statement to guide the responsible use of LLMs and AI in research and education. Samarawickrama (2022) discusses the importance of AI ethics and governance for an AI-enabled sustainable future. Tong et al. (2024) address the need for industry standards in AIED to address ethical governance and other challenges. Pozdniakov et al. (2024) propose a transition from conversational user interfaces to user-friendly applications for incorporating GenAI in educational tools. Wang et al. (2023) examine university responses to GenAI, finding an open but cautious approach. Sorathiya and Ginde (2024) conduct a systematic literature review of ethical requirements identification techniques for software. Wu et al. (2023) explore the security, privacy, and ethical implications of ChatGPT. Gupta et al. (2022) report on progress in AI ethics research, including privacy, bias, and AI design. Khan et al. (2022) survey AI practitioners and lawmakers on AI ethics principles and challenges. Fu et al. (2021) outline an ethical framework for AI and suggest recommendations for mitigating climate and privacy crises. Chan and Hu (2023) explore university students' perceptions of GenAI in higher education. Kimera et al. (2024) discuss ethical challenges in Neural Machine Translation. Kumar et al. (2024) explore ethical challenges related to security threats to Large Language Models. Chan (2024) explores the phenomenon of "AI guilt" among secondary school students. Oniani et al. (2023) propose ethical principles for generative AI in healthcare. Ardito (2023) critically analyzes generative AI detection tools in higher education. Porayska-Pomsta et al. (2024) discuss key ethical dimensions of AI in Education. Molina et al. (2024) discuss ethical considerations and use cases for generative AI in education, particularly within atmospheric sciences. Jacques et al. (2024) examine the transformative role of generative AI in higher education. Pappagallo (2024) synthesizes literature on the application of chatbots in e-learning, highlighting ethical considerations and proposing a new Socratic method for chatbot interactions.

This diverse body of research demonstrates the growing awareness of ethical challenges posed by AI in education. Future research should prioritize developing practical solutions for addressing data privacy concerns, mitigating algorithmic bias, establishing clear ethical guidelines, and fostering transparent and inclusive AI governance frameworks. Collaboration between researchers, educators, policymakers, and AI developers is essential to ensure the responsible and ethical integration of AI in education, ultimately maximizing its potential while safeguarding the rights and well-being of all learners.

References:

1. Karpouzis, K., 2024. Artificial Intelligence in Education: Ethical Considerations and Insights from Ancient Greek Philosophy. arXiv. Available at: http://arxiv.org/abs/2409.15296v1.
2. Adanyin, A., 2024. Ethical AI in Retail: Consumer Privacy and Fairness. arXiv. Available at: http://arxiv.org/abs/2410.15369v1.
3. Maity, S. & Deroy, A., 2024. Human-Centric eXplainable AI in Education. arXiv. Available at: http://arxiv.org/abs/2410.19822v1.
4. Daskalaki, E., Psaroudaki, K. & Fragopoulou, P., 2024. Navigating the Future of Education: Educators' Insights on AI Integration and Challenges in Greece, Hungary, Latvia, Ireland and Armenia. arXiv. Available at: http://arxiv.org/abs/2408.15686v1.
5. Mökander, J. et al., 2024. Challenges and Best Practices in Corporate AI Governance:Lessons from the Biopharmaceutical Industry. arXiv. Available at: http://arxiv.org/abs/2407.05339v1.
6. Porayska-Pomsta, K., 2024. From Algorithm Worship to the Art of Human Learning: Insights from 50-year journey of AI in Education. arXiv. Available at: http://arxiv.org/abs/2403.05544v1.
7. Lakkaraju, K. et al., 2024. Trust and ethical considerations in a multi-modal, explainable AI-driven chatbot tutoring system: The case of collaboratively solving Rubik's Cube. arXiv. Available at: http://arxiv.org/abs/2402.01760v2.
8. Mbiazi, D. et al., 2023. Survey on AI Ethics: A Socio-technical Perspective. arXiv. Available at: http://arxiv.org/abs/2311.17228v1.
9. Mougan, C. et al., 2022. Fairness Implications of Encoding Protected Categorical Attributes. arXiv. Available at: http://arxiv.org/abs/2201.11358v2.
10. Bulut, O. et al., 2024. The Rise of Artificial Intelligence in Educational Measurement: Opportunities and Ethical Challenges. arXiv. Available at: http://arxiv.org/abs/2406.18900v1.
11. Pant, A. et al., 2023. Ethics in the Age of AI: An Analysis of AI Practitioners' Awareness and Challenges. arXiv. Available at: http://arxiv.org/abs/2307.10057v1.
12. Rienties, B. et al., 2024. I would love this to be like an assistant, not the teacher: a voice of the customer perspective of what distance learning students want from an Artificial Intelligence Digital Assistant. arXiv. Available at: http://arxiv.org/abs/2403.15396v1.
13. Li, L. et al., 2023. ChatGPT in education: A discourse analysis of worries and concerns on social media. arXiv. Available at: http://arxiv.org/abs/2305.02201v1.
14. Chinta, S. et al., 2024. FairAIED: Navigating Fairness, Bias, and Ethics in Educational AI Applications. arXiv. Available at: http://arxiv.org/abs/2407.18745v1.
15. Chen, X., 2024. Analyses and Concerns in Precision Medicine: A Statistical Perspective. arXiv. Available at: http://arxiv.org/abs/2401.06899v1.

16. Gilbert, T., Brozek, M. & Brozek, A., 2023. Beyond Bias and Compliance: Towards Individual Agency and Plurality of Ethics in AI. arXiv. Available at: http://arxiv.org/abs/2302.12149v1.
17. Gikunda, K., 2023. Empowering Africa: An In-depth Exploration of the Adoption of Artificial Intelligence Across the Continent. arXiv. Available at: http://arxiv.org/abs/2401.09457v1.
18. Aydin, I. et al., 2024. Assessing Privacy Policies with AI: Ethical, Legal, and Technical Challenges. arXiv. Available at: http://arxiv.org/abs/2410.08381v1.
19. Kandasamy, U., 2024. Ethical Leadership in the Age of AI Challenges, Opportunities and Framework for Ethical Leadership. arXiv. Available at: http://arxiv.org/abs/2410.18095v2.
20. Melhart, D. et al., 2023. The Ethics of AI in Games. arXiv. Available at: http://arxiv.org/abs/2305.07392v1.
21. Sidiropoulos, D. & Anagnostopoulos, C.-N., 2024. Applications, challenges and ethical issues of AI and ChatGPT in education. arXiv. Available at: http://arxiv.org/abs/2402.07907v1.
22. Bin Emdad, F. et al., 2023. Towards A Unified Utilitarian Ethics Framework for Healthcare Artificial Intelligence. arXiv. Available at: http://arxiv.org/abs/2309.14617v1.
23. Ghimire, A. & Edwards, J., 2024. From Guidelines to Governance: A Study of AI Policies in Education. arXiv. Available at: http://arxiv.org/abs/2403.15601v1.
24. Zuber, N., Kacianka, S. & Gogoll, J., 2022. Big data ethics, machine ethics or information ethics? Navigating the maze of applied ethics in IT. arXiv. Available at: http://arxiv.org/abs/2203.13494v1.
25. Findlay, M. & Seah, J., 2020. An Ecosystem Approach to Ethical AI and Data Use: Experimental Reflections. arXiv. Available at: http://arxiv.org/abs/2101.02008v1.
26. Chen, J., Storchan, V. & Kurshan, E., 2021. Beyond Fairness Metrics: Roadblocks and Challenges for Ethical AI in Practice. arXiv. Available at: http://arxiv.org/abs/2108.06217v1.
27. Jiao, J. et al., 2024. Navigating LLM Ethics: Advancements, Challenges, and Future Directions. arXiv. Available at: http://arxiv.org/abs/2406.18841v3.
28. Findlater, L. et al., 2019. Fairness Issues in AI Systems that Augment Sensory Abilities. arXiv. Available at: http://arxiv.org/abs/1908.07333v1.
29. Ardabili, B. et al., 2023. Understanding Policy and Technical Aspects of AI-Enabled Smart Video Surveillance to Address Public Safety. arXiv. Available at: http://arxiv.org/abs/2302.04310v1.
30. Engelmann, S. et al., 2024. Visions of a Discipline: Analyzing Introductory AI Courses on YouTube. arXiv. Available at: http://arxiv.org/abs/2407.13077v1.
31. Karran, A. et al., 2024. Multi-stakeholder Perspective on Responsible Artificial Intelligence and Acceptability in Education. arXiv. Available at: http://arxiv.org/abs/2402.15027v2.

32. BaHammam, A. et al., 2023. Adapting to the Impact of AI in Scientific Writing: Balancing Benefits and Drawbacks while Developing Policies and Regulations. arXiv. Available at: http://arxiv.org/abs/2306.06699v1.
33. Samarawickrama, M., 2022. AI Governance and Ethics Framework for Sustainable AI and Sustainability. arXiv. Available at: http://arxiv.org/abs/2210.08984v1.
34. Tong, R. et al., 2024. Developing and Deploying Industry Standards for Artificial Intelligence in Education (AIED): Challenges, Strategies, and Future Directions. arXiv. Available at: http://arxiv.org/abs/2403.14689v2.
35. Pozdniakov, S. et al., 2024. Large Language Models Meet User Interfaces: The Case of Provisioning Feedback. arXiv. Available at: http://arxiv.org/abs/2404.11072v1.
36. Chan, C. & Tsi, L., 2023. The AI Revolution in Education: Will AI Replace or Assist Teachers in Higher Education?. arXiv. Available at: http://arxiv.org/abs/2305.01185v1.
37. Wang, H. et al., 2023. Generative AI in Higher Education: Seeing ChatGPT Through Universities' Policies, Resources, and Guidelines. arXiv. Available at: http://arxiv.org/abs/2312.05235v3.
38. Sorathiya, A. & Ginde, G., 2024. Ethical software requirements from user reviews: A systematic literature review. arXiv. Available at: http://arxiv.org/abs/2410.01833v1.
39. Wu, X., Duan, R. & Ni, J., 2023. Unveiling Security, Privacy, and Ethical Concerns of ChatGPT. arXiv. Available at: http://arxiv.org/abs/2307.14192v1.
40. Gupta, A. et al., 2022. State of AI Ethics Report (Volume 6, February 2022). arXiv. Available at: http://arxiv.org/abs/2202.07435v1.
41. Khan, A. et al., 2022. AI Ethics: An Empirical Study on the Views of Practitioners and Lawmakers. arXiv. Available at: http://arxiv.org/abs/2207.01493v2.
42. Fu, A. et al., 2021. P4AI: Approaching AI Ethics through Principlism. arXiv. Available at: http://arxiv.org/abs/2111.14062v1.
43. Chan, C. & Hu, W., 2023. Students' Voices on Generative AI: Perceptions, Benefits, and Challenges in Higher Education. arXiv. Available at: http://arxiv.org/abs/2305.00290v1.
44. Kimera, R., Kim, Y.-S. & Choi, H., 2024. Advancing AI with Integrity: Ethical Challenges and Solutions in Neural Machine Translation. arXiv. Available at: http://arxiv.org/abs/2404.01070v1.
45. Kumar, A. et al., 2024. The Ethics of Interaction: Mitigating Security Threats in LLMs. arXiv. Available at: http://arxiv.org/abs/2401.12273v2.
46. Chan, C., 2024. Exploring the Factors of "AI Guilt" Among Students -- Are You Guilty of Using AI in Your Homework?. arXiv. Available at: http://arxiv.org/abs/2407.10777v1.
47. Oniani, D. et al., 2023. From Military to Healthcare: Adopting and Expanding Ethical Principles for Generative Artificial Intelligence. arXiv. Available at: http://arxiv.org/abs/2308.02448v1.

48. Ardito, C., 2023. Contra generative AI detection in higher education assessments. arXiv. Available at: http://arxiv.org/abs/2312.05241v2.
49. Porayska-Pomsta, K., Holmes, W. & Nemorin, S., 2024. The Ethics of AI in Education. arXiv. Available at: http://arxiv.org/abs/2406.11842v1.
50. Molina, M. et al., 2024. Using Generative Artificial Intelligence Creatively in the Classroom: Examples and Lessons Learned. arXiv. Available at: http://arxiv.org/abs/2409.05176v1.
51. Jacques, P.H., Moss, H.K. & Garger, J., 2024. A Synthesis of AI in Higher Education: Shaping the Future. Journal of Behavioral and Applied Management, 24(2). Available at: https://doi.org/10.21818/001c.122146.
52. Pappagallo, S., 2024. Chatbots in Education: A Dual Perspective on Innovation and Ethics. Journal of Digital Pedagogy, 3(1), pp.3–10. Available at: https://doi.org/10.61071/jdp.2420.

9b: What ethical challenges arise from AI's role in education, particularly concerning data privacy and algorithmic bias?

Execution time: 54.07

The integration of artificial intelligence (AI) into education presents significant ethical challenges, particularly concerning data privacy and algorithmic bias. This literature review examines these challenges, drawing on recent research to provide a comprehensive overview of the ethical landscape of AI in education.

Several studies highlight the growing concerns surrounding data privacy in AI-driven educational settings. Daskalaki et al. (2024) found that while educators recognize the potential of AI, they also express concerns about its impact on student privacy, particularly regarding the collection and use of student data. Similarly, Adanyin (2024) reveals consumer anxieties about data collection and management by AI systems in retail, highlighting a broader societal concern about data privacy that extends to the educational context. Mökander et al. (2024) further emphasize the need for robust data privacy protocols within organizations implementing AI, offering practical guidance for operationalizing AI governance and risk management. These concerns are echoed by Rousi et al. (2024), who identify data privacy as a key ethical challenge arising from the use of large language models (LLMs) in multi-robot systems, underscoring the need for careful consideration of data protection in diverse AI applications.

Algorithmic bias is another critical ethical challenge in AIEd. Karpouzis (2024) explores the ethical implications of AI in education, drawing on ancient Greek philosophy to address concerns about algorithmic bias and its potential to perpetuate inequalities. Adanyin (2024) also identifies fairness as a major concern among consumers regarding AI systems, suggesting that algorithmic bias can lead to unequal treatment and erode trust. Maity and Deroy (2024) emphasize the importance of explainable AI (XAI) in education to address issues of transparency and trust, arguing that understanding how AI systems function is crucial for mitigating bias and ensuring fairness. Daskalaki et al. (2024) further reveal educators' concerns about AI's potential to expose students to biased data, highlighting the need for careful curation and oversight of AI-driven educational resources.

Beyond data privacy and algorithmic bias, the literature also addresses broader ethical considerations related to AI in education. Porayska-Pomsta (2024) explores the complex and often conflicting narratives surrounding AI in education, emphasizing the need for clarity and evidence-based practices to navigate the ethical implications of AIEd. This includes addressing concerns about the devaluation of non-STEM subjects and the potential impact of AI on human cognitive and socio-emotional development. Rousi et al. (2024) further highlight the emergence of novel ethical challenges with the advent of generative AI and LLMs, emphasizing the need for ongoing ethical reflection and development in this rapidly evolving field. Finally, Mökander et al. (2024) offer practical recommendations for organizations seeking to implement AI ethically, emphasizing the importance of continuous education and change management to ensure responsible AI practices. These studies collectively underscore the complex ethical landscape of AI in education and the need for ongoing research and dialogue to ensure that AI serves the best interests of all learners.

The ethical implications of artificial intelligence (AI) in education, particularly concerning data privacy and algorithmic bias, are increasingly critical as AI systems become more integrated into learning environments. This literature review synthesizes current research to explore these challenges.

One primary concern revolves around data privacy, especially when dealing with vulnerable populations like high school students. Lakkaraju et al. (2024) highlight the importance of informed consent from children, parents, and teachers in managing data within AI-driven educational platforms. Their work on the ALLURE chatbot emphasizes the need for age-appropriate language and mechanisms to steer interactions away from potentially harmful situations, demonstrating a practical approach to addressing data privacy and safety concerns in a specific educational context. Broader ethical concerns surrounding AI deployment, including fairness, privacy, accountability, safety, transparency, and environmental impact, are comprehensively addressed by Mbiazi et al. (2023). This work underscores the need for a holistic approach to ethical AI considerations, encompassing both technical and social perspectives, and acknowledges the growing interest of governments in establishing ethical guidelines for AI deployment.

Algorithmic bias presents another significant challenge. Mougan et al. (2022) investigate the impact of encoding methods on fairness and accuracy in machine learning models. Their comparison of one-hot encoding and target encoding reveals how these methods can introduce both irreducible and reducible bias, potentially leading to unfair outcomes. This research highlights the importance of carefully considering data preprocessing techniques to mitigate bias and ensure equitable outcomes. Bulut et al. (2024) further explore the ethical implications of AI in educational measurement, focusing on issues of validity, reliability, transparency, fairness, and equity. They address the risks of perpetuating inequalities through algorithmic bias and the lack of transparency in AI decision-making, emphasizing the need for ethical guidelines and ongoing research to ensure responsible AI use in assessment.

The practical challenges of implementing ethical AI in education are also addressed in the literature. Pant et al. (2023) investigate AI practitioners' perspectives on AI ethics, revealing that while awareness of ethical principles exists, challenges remain in incorporating them into AI systems. These challenges include general, technology-related, and human-related obstacles, highlighting the need for further research and practical guidance for developers. Rienties et al. (2024) explore student perceptions of AI in distance learning through a mixed-methods study. While students acknowledged the benefits of AI tools, they also expressed concerns about ethical implications, data privacy, academic integrity, and the future of education. This research underscores the importance of considering student perspectives when designing and implementing AI systems in educational settings.

Finally, Li et al. (2023) analyze Twitter data to gauge public perception and concerns regarding the use of ChatGPT in education. Their findings reveal concerns related to academic integrity, learning outcomes, limitations of AI capabilities, policy and social implications, and workforce challenges. This research highlights the importance of ongoing public discourse and collaboration among stakeholders to address the evolving ethical challenges posed by AI in education. Taken together, these studies emphasize the complex interplay of data privacy, algorithmic bias, and ethical considerations in the increasing use of AI in education, providing valuable insights for researchers and practitioners alike.

The ethical implications of Artificial Intelligence (AI) in education, particularly concerning data privacy and algorithmic bias, are increasingly critical as AI systems become more integrated into learning environments. Chinta et al. (2024) provide a comprehensive overview of algorithmic fairness in education, highlighting how various biases, including data-related, algorithmic, and user-interaction biases, can undermine equitable outcomes. Their work emphasizes the importance of mitigation techniques, ethical considerations, and legal frameworks in creating a fairer educational landscape, while also acknowledging persistent challenges like balancing fairness and accuracy and the need for diverse datasets. This resonates with the broader discussion of ethical AI development, as explored by Gilbert et al. (2023), who argue for a value-centered approach to AI ethics, emphasizing the crucial role of data labeling in shaping AI behavior. They advocate for user control over algorithms to build trust and address the widespread distrust stemming from current AI solutions.

The practical application of AI in diverse contexts, including education, raises further ethical concerns. Gikunda (2023) examines the adoption of AI in Africa, highlighting its potential in various sectors like healthcare, agriculture, and education, while also addressing ethical considerations such as data privacy and algorithmic bias. This regional perspective underscores the importance of considering cultural factors and infrastructural constraints when deploying AI solutions. Similarly, Jacques et al. (2024) explore the transformative role of generative AI in higher education, acknowledging the ethical dilemmas surrounding data privacy, security, and algorithmic bias that accompany its integration. Their work emphasizes the need for robust policies and ongoing research to ensure responsible AI implementation in educational settings.

The issue of data privacy is further explored by Aydin et al. (2024), who investigate the use of Large Language Models (LLMs) to assess privacy policies. Their research highlights the technical, ethical, and legal challenges of using LLMs for this purpose, contributing to the broader discussion of transparency and user agency in the age of AI. This connects to the challenges of ethical leadership in AI adoption, as discussed by Kandasamy (2024). This research emphasizes the importance of ethical leadership in navigating the challenges and opportunities presented by AI, advocating for a framework that incorporates fairness, transparency, and sustainability. Finally, while not directly focused on education, Chen (2024) discusses the ethical considerations of data privacy and security within the context of precision medicine, highlighting the challenges of data integration and interpretation from diverse sources. This underscores the broader importance of data governance and ethical considerations across various applications of AI, including education, where similar data privacy concerns are paramount.

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Finally, Li et al. (2023) analyze Twitter data to gauge public perception and concerns regarding the use of ChatGPT in education. Their findings reveal concerns related to academic integrity, learning outcomes, limitations of AI capabilities, policy and social implications, and workforce challenges. This research highlights the importance of ongoing public discourse and collaboration among stakeholders to address the evolving ethical challenges posed by AI in education. Taken together, these studies emphasize the complex interplay of data privacy, algorithmic bias, and ethical considerations in the increasing use of AI in education, providing valuable insights for researchers and practitioners alike.

The ethical implications of Artificial Intelligence (AI) in education, particularly concerning data privacy and algorithmic bias, are increasingly critical as AI systems become more integrated into learning environments. Chinta et al. (2024) provide a comprehensive overview of algorithmic fairness in education, highlighting how various biases, including data-related, algorithmic, and user-interaction biases, can undermine equitable outcomes. Their work emphasizes the importance of mitigation techniques, ethical considerations, and legal frameworks in creating a fairer educational landscape, while also acknowledging persistent challenges like balancing fairness and accuracy and the need for diverse datasets. This resonates with the broader discussion of ethical AI development, as explored by Gilbert et al. (2023), who argue for a value-centered approach to AI ethics, emphasizing the crucial role of data labeling in shaping AI behavior. They advocate for user control over algorithms to build trust and address the widespread distrust stemming from current AI solutions.

The practical application of AI in diverse contexts, including education, raises further ethical concerns. Gikunda (2023) examines the adoption of AI in Africa, highlighting its potential in various sectors like healthcare, agriculture, and education, while also addressing ethical considerations such as data privacy and algorithmic bias. This regional perspective underscores the importance of considering cultural factors and infrastructural constraints when deploying AI solutions. Similarly, Jacques et al. (2024) explore the transformative role of generative AI in higher education, acknowledging the ethical dilemmas surrounding data privacy, security, and algorithmic bias that accompany its integration. Their work emphasizes the need for robust policies and ongoing research to ensure responsible AI implementation in educational settings.

The issue of data privacy is further explored by Aydin et al. (2024), who investigate the use of Large Language Models (LLMs) to assess privacy policies. Their research highlights the technical, ethical, and legal challenges of using LLMs for this purpose, contributing to the broader discussion of transparency and user agency in the age of AI. This connects to the challenges of ethical leadership in AI adoption, as discussed by Kandasamy (2024). This research emphasizes the importance of ethical leadership in navigating the challenges and opportunities presented by AI, advocating for a framework that incorporates fairness, transparency, and sustainability. Finally, while not directly focused on education, Chen (2024) discusses the ethical considerations of data privacy and security within the context of precision medicine, highlighting the challenges of data integration and interpretation from diverse sources. This underscores the broader importance of data governance and ethical considerations across various applications of AI, including education, where similar data privacy concerns are paramount.

References:

1. Karpouzis, K., 2024. Artificial Intelligence in Education: Ethical Considerations and Insights from Ancient Greek Philosophy. arXiv. Available at: http://arxiv.org/abs/2409.15296v1.
2. Adanyin, A., 2024. Ethical AI in Retail: Consumer Privacy and Fairness. arXiv. Available at: http://arxiv.org/abs/2410.15369v1.
3. Maity, S. & Deroy, A., 2024. Human-Centric eXplainable AI in Education. arXiv. Available at: http://arxiv.org/abs/2410.19822v1.
4. Daskalaki, E., Psaroudaki, K. & Fragopoulou, P., 2024. Navigating the Future of Education: Educators' Insights on AI Integration and Challenges in Greece, Hungary, Latvia, Ireland and Armenia. arXiv. Available at: http://arxiv.org/abs/2408.15686v1.
5. Mökander, J. et al., 2024. Challenges and Best Practices in Corporate AI Governance:Lessons from the Biopharmaceutical Industry. arXiv. Available at: http://arxiv.org/abs/2407.05339v1.
6. Rousi, R. et al., 2024. GPT versus Humans: Uncovering Ethical Concerns in Conversational Generative AI-empowered Multi-Robot Systems. arXiv. Available at: http://arxiv.org/abs/2411.14009v1.
7. Porayska-Pomsta, K., 2024. From Algorithm Worship to the Art of Human Learning: Insights from 50-year journey of AI in Education. arXiv. Available at: http://arxiv.org/abs/2403.05544v1.
8. Lakkaraju, K. et al., 2024. Trust and ethical considerations in a multi-modal, explainable AI-driven chatbot tutoring system: The case of collaboratively solving Rubik's Cube. arXiv. Available at: http://arxiv.org/abs/2402.01760v2.
9. Mbiazi, D. et al., 2023. Survey on AI Ethics: A Socio-technical Perspective. arXiv. Available at: http://arxiv.org/abs/2311.17228v1.

10. Mougan, C. et al., 2022. Fairness Implications of Encoding Protected Categorical Attributes. arXiv. Available at: http://arxiv.org/abs/2201.11358v2.
11. Bulut, O. et al., 2024. The Rise of Artificial Intelligence in Educational Measurement: Opportunities and Ethical Challenges. arXiv. Available at: http://arxiv.org/abs/2406.18900v1.
12. Pant, A. et al., 2023. Ethics in the Age of AI: An Analysis of AI Practitioners' Awareness and Challenges. arXiv. Available at: http://arxiv.org/abs/2307.10057v1.
13. Rienties, B. et al., 2024. I would love this to be like an assistant, not the teacher: a voice of the customer perspective of what distance learning students want from an Artificial Intelligence Digital Assistant. arXiv. Available at: http://arxiv.org/abs/2403.15396v1.
14. Li, L. et al., 2023. ChatGPT in education: A discourse analysis of worries and concerns on social media. arXiv. Available at: http://arxiv.org/abs/2305.02201v1.
15. Chinta, S. et al., 2024. FairAIED: Navigating Fairness, Bias, and Ethics in Educational AI Applications. arXiv. Available at: http://arxiv.org/abs/2407.18745v1.
16. Chen, X., 2024. Analyses and Concerns in Precision Medicine: A Statistical Perspective. arXiv. Available at: http://arxiv.org/abs/2401.06899v1.
17. Gilbert, T., Brozek, M. & Brozek, A., 2023. Beyond Bias and Compliance: Towards Individual Agency and Plurality of Ethics in AI. arXiv. Available at: http://arxiv.org/abs/2302.12149v1.
18. Gikunda, K., 2023. Empowering Africa: An In-depth Exploration of the Adoption of Artificial Intelligence Across the Continent. arXiv. Available at: http://arxiv.org/abs/2401.09457v1.
19. Aydin, I. et al., 2024. Assessing Privacy Policies with AI: Ethical, Legal, and Technical Challenges. arXiv. Available at: http://arxiv.org/abs/2410.08381v1.
20. Kandasamy, U., 2024. Ethical Leadership in the Age of AI Challenges, Opportunities and Framework for Ethical Leadership. arXiv. Available at: http://arxiv.org/abs/2410.18095v2.
21. Jacques, P.H., Moss, H.K. & Garger, J., 2024. A Synthesis of AI in Higher Education: Shaping the Future. Journal of Behavioral and Applied Management, 24(2). Available at: https://doi.org/10.21818/001c.122146.
22. Pappagallo, S., 2024. Chatbots in Education: A Dual Perspective on Innovation and Ethics. Journal of Digital Pedagogy, 3(1), pp.3–10. Available at: https://doi.org/10.61071/jdp.2420.

10a: How does AI influence students' preparedness for future academic and career challenges?

Execution time: 74.06

How does AI influence students' preparedness for future academic and career challenges? This review examines the multifaceted impact of AI on students' academic journeys and career readiness, drawing on a diverse body of research.

Several studies highlight the potential of AI to enhance student learning and performance. Bashiri and Kowsari (2024) explore how AI-driven social media platforms contribute to improved academic performance, enhanced critical thinking skills, and increased student engagement. Rasnayaka et al. (2024) demonstrate the usefulness of Large Language Models (LLMs) for software engineering students, particularly in generating foundational code and debugging, thus preparing them for AI-augmented software development careers. Chen et al. (2024) introduce GPTutor, a personalized learning platform using Generative AI to adapt educational content and practice exercises, fostering a more engaging and effective learning environment tailored to individual career aspirations. Similarly, Flores et al. (2024) emphasize the role of robotics groups in higher education in developing transversal skills like teamwork and problem-solving, crucial for future careers.

AI is also transforming career guidance and advising. Faruque et al. (2024) present an AI-assisted model for early career prediction, offering tailored suggestions to students based on their skills and interests. Assylzhan et al. (2023) develop an intelligent system using machine learning models to evaluate graduates' career readiness, offering a valuable tool for universities to enhance student preparation. Further, Patan et al. (2023) discuss the increasing demand for blockchain skills in various industries and emphasize the need for HEIs to adapt their curricula to prepare students for these emerging career paths. Similarly, Feder (2019) highlights the need for petroleum engineering education to adapt to industry changes, including the growing demand for AI and digital skills.

However, the integration of AI in education also presents challenges. Hirabayashi et al. (2024) reveal student concerns about AI's potential negative impact on job prospects, prompting the need for courses addressing the future implications of AI. Smith et al. (2024) explore computer science students' perceptions and uses of GenAI, acknowledging the need for university policies to adapt to these technologies. Eaton et al. (2017) explore how to incorporate ethical considerations into AI education, given the potential societal impacts of AI. Quinn and Coghlan (2021) discuss the urgency of incorporating medical AI ethics into medical curricula to equip future healthcare professionals with the necessary skills for safe and effective use of AI tools. Daskalaki et al. (2024) find that while educators are optimistic about AI's potential, they also express concerns about its impact on critical thinking and ethical issues, highlighting the need for professional development in AI. Zhang and Yang (2024) highlight the increasing use of ChatGPT for academic help-seeking, emphasizing the need for educators to cultivate students' critical thinking skills in light of potential biases and distortions in AI-generated information.

Beyond specific skill development, AI's influence extends to broader aspects of academic success. Burstein et al. (2018) propose the concept of “learning communities” facilitated by AI, which can significantly influence academic outcomes. Gao et al. (2021) explore the potential of AI to optimize classroom seating arrangements for maximizing student engagement. O'Shea et al. (2013) demonstrate the effectiveness of a physics curriculum focused on life sciences in increasing students' interest in physics and its relevance to their future careers. Baucks et al. (2024) introduce Differential Course Functioning (DCF) to identify inequities in course difficulty across student groups, enabling more equitable assessments of academic performance. Souto-Maior and Shroff (2023) employ advanced statistical techniques to address racial disparities in enrollment in advanced coursework, aiming to ensure equal opportunities. Ellis et al. (2015) investigate factors influencing persistence in calculus, a gateway course for STEM fields, highlighting the role of mathematical confidence in women's STEM career choices. Zhou et al. (2023) explore factors impacting STEM employment after graduation, including the role of undergraduate practicum and career services.

Furthermore, several studies examine the impact of AI on academic research and career progression. Wang et al. (2021) propose ACSeeker, a visual analytics approach to examine the influence of individual and social factors on academic career success. Deville et al. (2014) investigate scientists' mobility patterns and their impact on scientific outcomes. Penner et al. (2013) stress-test a career predictability model, highlighting its limitations in predicting the impact of early-career scientists. Bachmann et al. (2024) explore the role of “brokerage” in facilitating new collaborations and its impact on academic success. Duan et al. (2024) analyze the importance of postdoctoral training for early-career success in academia. Kim et al. (2022) propose new multi-agent reinforcement learning challenges in StarCraft to explore the capabilities of AI algorithms in complex, multi-stage tasks.

Finally, several studies address broader issues surrounding AI's impact on academia and student careers. Eran-Jona and Nir (2020) explore the implications of gender power structures on women's academic careers in physics. Bai et al. (2024) analyze the personality traits and career aspirations of physics undergraduates, revealing correlations between personality type and academic intent. Verostek et al. (2023)

investigate how graduate students search for research advisors and identify disparities in departmental support. Chen (2022) proposes PreDefense, a mentorship program to guide underrepresented students through the academic conference process, protecting them from predatory practices and supporting their research careers. Mao et al. (2023) examine persistence in machine learning and AI fields, highlighting the importance of belonging and mentorship. Dalziel et al. (2024) provide a comprehensive overview of AI's societal and academic impacts, including implications for social work education. Andreeva and Savova (2024) investigate law students' AI usage and their perspectives on its role in the legal field, stressing the need for greater engagement with AI technologies among aspiring legal professionals. Suriyaarachchi et al. (2023) explore the impact of hands-on programming workshops using sensors on high school students' self-efficacy and outcome expectancy, emphasizing the importance of positive experiences for underrepresented groups in computer science. Boumi and Vela (2022) utilize Hidden Markov Models to analyze student academic trajectories, providing insights into the relationship between academic performance and graduation rates. Huang et al. (2024) investigate the impact of cross-border recruitment programs on early-career STEM scholars' performance and career development. Matei and Bertino (2023) examine cybersecurity professionals' and educators' perceptions of students' preparedness for the AI-driven cybersecurity landscape, emphasizing the importance of ethics, systems thinking, and communication skills. Richards and Kelly (2024) explore astronomy identity formation among undergraduate students, highlighting the importance of inclusive communities and mentorship in facilitating access to astronomy careers. Awaji et al. (2020) propose a blockchain-based system for verifiable academic achievements, offering benefits for students, employers, and higher education institutions. Thuseethan and Kuhanesan (2015) examine the impact of Facebook usage on university students' academic performance, highlighting the potential negative consequences of excessive social media use. Giunchiglia et al. (2020) quantitatively analyze the correlation between social media usage and academic performance using smartphone logs, further reinforcing the need to manage social media use for academic success. Yang (2021) introduces the concept of “academic lobification,” highlighting the need to understand students' strategic performance management for more accurate assessment and talent identification. Graur (2018) emphasizes the benefits of mentoring programs in providing high-school students with research experience and preparing early-career scientists for advising roles in academia. Alaee and Zwickl (2024) examine how undergraduate physics majors develop interest in specific subfields, providing valuable insights for physics departments and career guidance professionals. Katsamakas et al. (2024) use a complex systems approach to analyze the AI transformation of higher education institutions, highlighting the need for strategic leadership in navigating this complex landscape. Capretz et al. (2022) investigate software students' perceptions of software testing careers across different Asian countries, revealing cultural differences and the need to promote a positive view of testing as a challenging and intellectually stimulating career path. Paz (2023) analyzes academic performance variables impacting dropout rates in civil engineering, informing retention strategies. Barradell (2022) discusses the evolving concept of "preparedness" in health professional education, advocating for a shift towards "stewardship" to better equip graduates for the complexities of healthcare practice.

This literature review demonstrates that AI has a profound and multifaceted influence on student preparedness for future academic and career challenges, offering both opportunities and challenges for educators, institutions, and policymakers. Further research is needed to fully understand the long-term implications of AI in education and to develop effective strategies for maximizing its benefits while mitigating potential risks.

References:

1. Assylzhan, I. et al., 2023. Intelligent System for Assessing University Student Personality Development and Career Readiness. arXiv. Available at: http://arxiv.org/abs/2308.15620v1.
2. Bashiri, M. & Kowsari, K., 2024. Transformative Influence of LLM and AI Tools in Student Social Media Engagement: Analyzing Personalization, Communication Efficiency, and Collaborative Learning. arXiv. Available at: http://arxiv.org/abs/2407.15012v1.
3. Faruque, S., Khushbu, S. & Akter, S., 2024. Unlocking Futures: A Natural Language Driven Career Prediction System for Computer Science and Software Engineering Students. arXiv. Available at: http://arxiv.org/abs/2405.18139v1.
4. Hirabayashi, S. et al., 2024. Harvard Undergraduate Survey on Generative AI. arXiv. Available at: http://arxiv.org/abs/2406.00833v2.
5. Bai, S., Chen, W. & Gao, Z., 2024. Exploring the MBTI distribution among Chinese undergraduate physics students: the influence of family income on career trajectories. arXiv. Available at: http://arxiv.org/abs/2411.01379v1.
6. Eran-Jona, M. & Nir, Y., 2020. The academic career in physics as a "deal": Choosing physics within a gendered power structure and excellence as an extra hurdle for women. arXiv. Available at: http://arxiv.org/abs/2010.13115v1.
7. Wasil, A. et al., 2024. AI Emergency Preparedness: Examining the federal government's ability to detect and respond to AI-related national security threats. arXiv. Available at: http://arxiv.org/abs/2407.17347v2.

8. Flores, G. et al., 2024. De la Extensión a la Investigación: Como La Robótica Estimula el Interés Académico en Estudiantes de Grado. arXiv. Available at: http://arxiv.org/abs/2411.05011v1.
9. Mao, K. et al., 2023. "Just a little bit on the outside for the whole time": Social belonging confidence and the persistence of Machine Learning and Artificial Intelligence students. arXiv. Available at: http://arxiv.org/abs/2311.10745v1.
10. Chen, T., 2022. PreDefense: Defending Underserved AI Students and Researchers from Predatory Conferences. arXiv. Available at: http://arxiv.org/abs/2201.13268v1.
11. Verostek, M., Miller, C. & Zwickl, B., 2023. Inequities and misaligned expectations in PhD students' search for a research group. arXiv. Available at: http://arxiv.org/abs/2307.07008v1.
12. Wang, Y. et al., 2021. Seek for Success: A Visualization Approach for Understanding the Dynamics of Academic Careers. arXiv. Available at: http://arxiv.org/abs/2108.03381v2.
13. Souto-Maior, J. & Shroff, R., 2023. Differences in academic preparedness do not fully explain Black-White enrollment disparities in advanced high school coursework. arXiv. Available at: http://arxiv.org/abs/2306.15075v2.
14. Ellis, J., Fosdick, B. & Rasmussen, C., 2015. Women 1.5 Times More Likely to Leave STEM Pipeline After Calculus Compared to Men: Lack of Mathematical Confidence a Potential Culprit. arXiv. Available at: http://arxiv.org/abs/1510.07541v1.
15. Quinn, T. & Coghlan, S., 2021. Readying Medical Students for Medical AI: The Need to Embed AI Ethics Education. arXiv. Available at: http://arxiv.org/abs/2109.02866v1.
16. Katsamakas, E., Pavlov, O. & Saklad, R., 2024. Artificial intelligence and the transformation of higher education institutions. arXiv. Available at: http://arxiv.org/abs/2402.08143v1.
17. Capretz, L. et al., 2022. Social Aspects of Software Testing: Comparative Studies in Asia. arXiv. Available at: http://arxiv.org/abs/2205.07781v1.
18. Baucks, F. et al., 2024. Gaining Insights into Group-Level Course Difficulty via Differential Course Functioning. arXiv. Available at: http://arxiv.org/abs/2406.04348v1.
19. Rasnayaka, S. et al., 2024. An Empirical Study on Usage and Perceptions of LLMs in a Software Engineering Project. arXiv. Available at: http://arxiv.org/abs/2401.16186v1.
20. Burstein, D., Kenter, F. & Shi, F., 2018. Leveraging local network communities to predict academic performance. arXiv. Available at: http://arxiv.org/abs/1810.04730v1.
21. Dalziel, M., Schaffer, K. & Martin, N., 2024. Navigating AI in Social Work and Beyond: A Multidisciplinary Review. arXiv. Available at: http://arxiv.org/abs/2411.07245v1.
22. Daskalaki, E., Psaroudaki, K. & Fragopoulou, P., 2024. Navigating the Future of Education: Educators' Insights on AI Integration and Challenges in Greece, Hungary, Latvia, Ireland and Armenia. arXiv. Available at: http://arxiv.org/abs/2408.15686v1.

23. Andreeva, D. & Savova, G., 2024. Artificial Intelligence in the Legal Field: Law Students Perspective. arXiv. Available at: http://arxiv.org/abs/2410.09937v1.
24. Suriyaarachchi, H. et al., 2023. Using Sensor-Based Programming to Improve Self-Efficacy and Outcome Expectancy for Students from Underrepresented Groups. arXiv. Available at: http://arxiv.org/abs/2304.06279v1.
25. Boumi, S. & Vela, A., 2022. Impacts of Students Academic Performance Trajectories on Final Academic Success. arXiv. Available at: http://arxiv.org/abs/2201.08744v1.
26. Huang, Y. et al., 2024. Talent hat, cross-border mobility, and career development in China. arXiv. Available at: http://arxiv.org/abs/2403.00107v1.
27. Matei, S. & Bertino, E., 2023. Educating for AI Cybersecurity Work and Research: Ethics, Systems Thinking, and Communication Requirements. arXiv. Available at: http://arxiv.org/abs/2311.04326v1.
28. Richards, Z. & Kelly, A., 2024. Astronomy Identity Framework for Undergraduate Students and Researchers. arXiv. Available at: http://arxiv.org/abs/2410.00885v1.
29. Patan, R. et al., 2023. Blockchain Education: Current State, Limitations, Career Scope, Challenges, and Future Directions. arXiv. Available at: http://arxiv.org/abs/2301.07889v1.
30. Kim, M. et al., 2022. The StarCraft Multi-Agent Challenges+ : Learning of Multi-Stage Tasks and Environmental Factors without Precise Reward Functions. arXiv. Available at: http://arxiv.org/abs/2207.02007v2.
31. Thuseethan, S. & Kuhanesan, S., 2015. Influence of Facebook in Academic Performance of Sri Lankan University Students. arXiv. Available at: http://arxiv.org/abs/1501.00528v1.
32. Chen, E. et al., 2024. GPTutor: Great Personalized Tutor with Large Language Models for Personalized Learning Content Generation. arXiv. Available at: http://arxiv.org/abs/2407.09484v1.
33. Deville, P. et al., 2014. Career on the Move: Geography, Stratification, and Scientific Impact. arXiv. Available at: http://arxiv.org/abs/1404.6247v1.
34. Awaji, B., Solaiman, E. & Marshall, L., 2020. Blockchain-Based Trusted Achievement Record System Design. arXiv. Available at: http://arxiv.org/abs/2007.02161v1.
35. Zhang, M. & Yang, X., 2024. Google or ChatGPT: Who is the Better Helper for University Students. arXiv. Available at: http://arxiv.org/abs/2405.00341v1.
36. Zhou, L., Stratton, D. & Li, X., 2023. Retention in STEM: Factors Influencing Student Persistence and Employment. arXiv. Available at: http://arxiv.org/abs/2311.14142v2.
37. Gao, N. et al., 2021. Individual and Group-wise Classroom Seating Experience: Effects on Student Engagement in Different Courses. arXiv. Available at: http://arxiv.org/abs/2112.12342v3.

38. O'Shea, B., Terry, L. & Benenson, W., 2013. From F=ma to Flying Squirrels: Curricular Change in an Introductory Physics Course. arXiv. Available at: http://arxiv.org/abs/1305.1398v1.
39. Giunchiglia, F. et al., 2020. Mobile social media usage and academic performance. arXiv. Available at: http://arxiv.org/abs/2004.01392v1.
40. Yang, S., 2021. Academic Lobification: Low-performance Control Strategy for Long-planed Academic Purpose. arXiv. Available at: http://arxiv.org/abs/2111.13590v1.
41. Graur, O., 2018. The Harvard Science Research Mentoring Program. arXiv. Available at: http://arxiv.org/abs/1809.08078v2.
42. Alaee, D. & Zwickl, B., 2024. Exploring Subfield Interest Development in Undergraduate Physics Students through Social Cognitive Career Theory. arXiv. Available at: http://arxiv.org/abs/2407.07808v1.
43. Bachmann, J. et al., 2024. Cumulative Advantage of Brokerage in Academia. arXiv. Available at: http://arxiv.org/abs/2407.11909v1.
44. Penner, O. et al., 2013. The case for caution in predicting scientists' future impact. arXiv. Available at: http://arxiv.org/abs/1304.0627v1.
45. Smith, C. et al., 2024. Early Adoption of Generative Artificial Intelligence in Computing Education: Emergent Student Use Cases and Perspectives in 2023. arXiv. Available at: http://arxiv.org/abs/2411.11166v1.
46. Yang, X. et al., 2023. Cautious explorers generate more future academic impact. arXiv. Available at: http://arxiv.org/abs/2306.16643v2.
47. Hu, Q. & Rangwala, H., 2019. Academic Performance Estimation with Attention-based Graph Convolutional Networks. arXiv. Available at: http://arxiv.org/abs/2001.00632v1.
48. Paz, H., 2023. College Dropout Factors: An Analysis with LightGBM and Shapley's Cooperative Game Theory. arXiv. Available at: http://arxiv.org/abs/2311.06260v1.
49. Duan, Y. et al., 2024. Where postdoctoral journeys lead. arXiv. Available at: http://arxiv.org/abs/2411.03938v1.
50. Eaton, E. et al., 2017. Blue Sky Ideas in Artificial Intelligence Education from the EAAI 2017 New and Future AI Educator Program. arXiv. Available at: http://arxiv.org/abs/1702.00137v1.
51. Barradell, S., 2022. Reimagining Preparedness of Health Professional Graduates Through Stewardship. Teaching and Learning in Medicine, 35(4), pp.486–495. Available at: https://doi.org/10.1080/10401334.2022.2148108.
52. Feder, J., 2019. As Industry Changes, So Does Petroleum Engineering Education. Journal of Petroleum Technology, 71(12), pp.44–48. Available at: https://doi.org/10.2118/1219-0044-jpt.

10b: How does AI influence students' preparedness for future academic and career challenges?

Execution time: 73.46

This literature review examines the influence of AI on students' preparedness for future academic and career challenges. Several studies highlight the multifaceted impact of AI, ranging from enhancing learning experiences to raising concerns about future job prospects and societal implications.

Assylzhan et al. (2023) developed an intelligent system using machine learning models and fuzzy sets to predict graduates' career readiness based on factors like satisfaction with education and salary expectations. This system offers universities a valuable tool for assessing and improving student preparedness for post-graduation challenges by identifying key contributing factors and refining curricula accordingly. Bashiri and Kowsari (2024) explored the transformative role of AI-powered tools, particularly Large Language Models (LLMs), in social media for students. Their research, based on UniversityCube data, suggests that AI-enhanced platforms can improve academic performance, critical thinking, and collaborative engagement by providing personalized content and fostering supportive online communities. Faruque et al. (2024) focused on developing an AI-assisted model for early career prediction, specifically for Computer Science and Software Engineering students. By leveraging NLP techniques and machine learning algorithms, this model analyzes student skills and interests to provide tailored career suggestions, thereby enhancing educational advising and assisting students in finding suitable job matches.

Hirabayashi et al. (2024) investigated the impact of generative AI on Harvard undergraduates, revealing its widespread use and its influence on study habits, class choices, and career prospects. The study also highlighted student concerns about AI's potential negative impact on job prospects and broader societal implications, such as economic inequality and existential risks. Bai et al. (2024) examined the relationship between MBTI personality types, career aspirations, and mental health among physics undergraduates. Their findings suggest a correlation between certain personality types (INTJ, INTP) and a preference for academic research, contributing to a deeper understanding of how personality influences career paths. Eran-Jona and Nir (2020) explored the gender imbalance in physics academia, revealing how latent power structures and societal expectations influence women's career decisions and create barriers to their advancement. The study emphasizes the need to address these systemic issues to promote gender equality in the field.

Finally, Wasil et al. (2024) addressed the crucial issue of AI emergency preparedness, focusing on the federal government's ability to detect and respond to national security threats related to AI. By analyzing plausible risk scenarios, such as loss of control over powerful AI systems and cybersecurity threats, the research offers recommendations for improving emergency preparedness and mitigating potential risks associated with AI advancements. These studies collectively demonstrate the complex and multifaceted influence of AI on students' preparedness for future challenges, highlighting both the opportunities and potential risks associated with this rapidly evolving technology. Further research is needed to fully understand the long-term implications of AI on education, career paths, and society as a whole.

How does AI influence students' preparedness for future academic and career challenges? This literature review explores this question by examining the impact of AI-related fields and technologies on various aspects of student development, from technical skills acquisition to academic persistence and mentorship.

The emergence of AI and machine learning (ML) presents a novel context for understanding student persistence in STEM fields. Mao et al. (2023) conducted exploratory interviews with students in ML/AI courses, revealing that students' perceptions of a career in these fields diverge based on their interest and programming confidence. Factors such as exposure to the field, interpretations of its boundaries, and beliefs about necessary skills influence students' intentions to persist. The study highlights the importance of social belonging and close mentorship in fostering persistence, suggesting avenues for future research focusing on these aspects, intersectional identity, and introductory courses. Complementing this focus on persistence, Chen (2022) emphasizes the critical role of mentorship in maintaining diversity within the AI community, particularly for underserved students. The study underscores the need for guidance in navigating the conference and publication process, especially given the rise of predatory conferences. The proposed PreDefense mentorship program aims to equip students with the skills to identify legitimate venues and prepare them for ethical and successful research careers.

Beyond AI-specific fields, the influence of related technologies like robotics extends to broader skill development. Flores et al. (2024) investigated the impact of robotics groups in higher education, finding that participation significantly improves transversal skills such as teamwork, creativity, and problem-solving. Students involved in robotics also reinforced their theoretical knowledge and increased their interest in research and academic commitment, demonstrating the potential of educational robotics to promote active and collaborative learning. This resonates with the findings of Verostek et al. (2023), who examined the process of joining research groups, a crucial step in graduate education. Their comparative case study revealed disparities in students' perceptions of finding an advisor and inequities in available resources, highlighting the need for consistent advising throughout undergraduate and graduate experiences.

Furthermore, understanding academic career success in the context of rapidly evolving fields like AI requires a dynamic perspective. Wang et al. (2021) proposed ACSeeker, a visual analytics approach to explore the influence of individual and social factors on career success over time. This tool allows researchers to examine how the impact of these factors changes at different career stages, providing valuable insights for students navigating the complexities of academic pathways. Addressing potential barriers to academic success, Souto-Maior and Shroff (2023) investigated racial disparities in advanced coursework enrollment. Their study found that differences in prior academic preparation do not fully explain the underrepresentation of Black students in AP mathematics, suggesting the need to address inequities in coursework placement processes.

Finally, the gender gap in STEM fields remains a persistent challenge, and Ellis et al. (2015) examined its manifestation in calculus, a gateway course for many STEM disciplines. Their research revealed that women are more likely to be dissuaded from continuing in calculus than men, even after controlling for academic preparedness and career intentions. The study highlights the role of mathematical confidence, rather than ability, in women's departure from calculus, suggesting interventions focused on boosting confidence could significantly increase female representation in STEM.

In conclusion, this review demonstrates that AI influences students' preparedness for future academic and career challenges in multifaceted ways. From fostering persistence in AI-related fields to developing crucial transversal skills through robotics, AI and related technologies are reshaping the educational landscape. Addressing issues of mentorship, equitable access to resources, and fostering confidence are crucial for ensuring that all students can thrive in the age of AI.

How does AI influence students' preparedness for future academic and career challenges? This question is increasingly relevant given the rapid advancements and integration of AI across various disciplines. This literature review examines this question through the lens of several recent studies, exploring the impact of AI on student learning, curriculum development, and the evolving landscape of future professions.

One key area of concern is the integration of AI into professional training, particularly in fields like medicine. Quinn and Coghlan (2021) argue that medical education must adapt to the inevitable presence of AI in clinical practice. Their proposed Embedded AI Ethics Education Framework offers a practical approach to incorporating AI ethics into existing curricula, addressing the crucial "how" of implementation. This framework focuses on equipping students with the ethical considerations surrounding AI use, misuse, and abuse, ultimately enhancing their preparedness for responsible AI integration in healthcare.

Beyond specific professional fields, the transformative potential of AI in higher education as a whole is undeniable. Katsamakas et al. (2024) utilize a systems thinking approach to analyze the complex interplay of factors driving AI adoption in higher education institutions (HEIs). Their causal loop diagram highlights the potential for AI to enhance student learning, research, and administration, while also acknowledging challenges such as academic integrity and the shifting job market. This research underscores the need for HEIs to proactively address these challenges and equip students with AI-complementary skills to navigate the evolving professional landscape.

The influence of AI extends beyond simply using AI tools; it also impacts students' perceptions of future career paths. Capretz et al. (2022) investigate the motivations and demotivations influencing software students' career choices in software testing across different Asian countries. Their findings reveal varying levels of interest in testing careers, highlighting the importance of understanding cultural and regional influences on student perceptions of AI-related roles. This research emphasizes the need for educators to address these perceptions and promote a positive view of emerging career paths shaped by AI.

Furthermore, AI can be leveraged to analyze and improve curriculum design itself. Baucks et al. (2024) introduce Differential Course Functioning (DCF), an IRT-based methodology to identify disparities in course difficulty across different student groups. This approach allows for a more nuanced understanding of student performance and can inform targeted interventions to improve course preparedness and address equity gaps. By leveraging AI for curriculum analytics, institutions can better prepare students for academic success and ensure equitable access to learning opportunities.

The integration of AI into the learning process itself is also transforming how students acquire and apply knowledge. Rasnayaka et al. (2024) explore the use of Large Language Models (LLMs) by software engineering students. Their findings suggest that LLMs can be valuable tools in the early stages of software development, particularly for generating code structures and debugging. This research highlights the potential of AI to enhance student productivity and emphasizes the need for educational approaches that foster effective human-AI collaboration.

Beyond individual student performance, AI can also illuminate the dynamics of peer learning and collaboration. Burstein et al. (2018) propose a novel approach to predicting academic outcomes by identifying students' learning communities and treating academic success as a contagion. This research demonstrates the power of AI to analyze complex social networks and provide insights into how peer interactions influence student learning, offering valuable information for educators seeking to optimize collaborative learning environments.

Finally, the broader question of student preparedness for future challenges requires a re-evaluation of the very purpose of education. Barradell (2022) argues that traditional notions of preparedness may be inadequate in the face of rapid societal and technological change. This perspective challenges educators to move beyond a narrow focus on skills and knowledge acquisition and embrace a more holistic approach to preparing students for the complexities of future practice. This includes fostering adaptability, critical thinking, and a sense of stewardship for their chosen professions.

In conclusion, the reviewed literature demonstrates the multifaceted influence of AI on students' preparedness for future academic and career challenges. From integrating AI ethics into professional training to leveraging AI for curriculum analytics and fostering human-AI collaboration, these studies highlight the need for a proactive and adaptable approach to education in the age of AI. By embracing the transformative potential of AI while addressing its ethical and societal implications, educators can empower students to navigate the evolving landscape of future learning and work.

Literature Review: This literature review examines the influence of AI on students' preparedness for future academic and career challenges. Several studies highlight the multifaceted impact of AI, ranging from enhancing learning experiences to raising concerns about future job prospects and societal implications.

Assylzhan et al. (2023) developed an intelligent system using machine learning models and fuzzy sets to predict graduates' career readiness based on factors like satisfaction with education and salary expectations. This system offers universities a valuable tool for assessing and improving student preparedness for post-graduation challenges by identifying key contributing factors and refining curricula accordingly. Bashiri and Kowsari (2024) explored the transformative role of AI-powered tools, particularly Large Language Models (LLMs), in social media for students. Their research, based on UniversityCube data, suggests that AI-enhanced platforms can improve academic performance, critical thinking, and collaborative engagement by providing personalized content and fostering supportive online communities. Faruque et al. (2024) focused on developing an AI-assisted model for early career prediction, specifically for Computer

Science and Software Engineering students. By leveraging NLP techniques and machine learning algorithms, this model analyzes student skills and interests to provide tailored career suggestions, thereby enhancing educational advising and assisting students in finding suitable job matches.

Hirabayashi et al. (2024) investigated the impact of generative AI on Harvard undergraduates, revealing its widespread use and its influence on study habits, class choices, and career prospects. The study also highlighted student concerns about AI's potential negative impact on job prospects and broader societal implications, such as economic inequality and existential risks. Bai et al. (2024) examined the relationship between MBTI personality types, career aspirations, and mental health among physics undergraduates. Their findings suggest a correlation between certain personality types (INTJ, INTP) and a preference for academic research, contributing to a deeper understanding of how personality influences career paths. Eran-Jona and Nir (2020) explored the gender imbalance in physics academia, revealing how latent power structures and societal expectations influence women's career decisions and create barriers to their advancement. The study emphasizes the need to address these systemic issues to promote gender equality in the field.

Finally, Wasil et al. (2024) addressed the crucial issue of AI emergency preparedness, focusing on the federal government's ability to detect and respond to national security threats related to AI. By analyzing plausible risk scenarios, such as loss of control over powerful AI systems and cybersecurity threats, the research offers recommendations for improving emergency preparedness and mitigating potential risks associated with AI advancements. These studies collectively demonstrate the complex and multifaceted influence of AI on students' preparedness for future challenges, highlighting both the opportunities and potential risks associated with this rapidly evolving technology. Further research is needed to fully understand the long-term implications of AI on education, career paths, and society as a whole.

How does AI influence students' preparedness for future academic and career challenges? This literature review explores this question by examining the impact of AI-related fields and technologies on various aspects of student development, from technical skills acquisition to academic persistence and mentorship.

The emergence of AI and machine learning (ML) presents a novel context for understanding student persistence in STEM fields. Mao et al. (2023) conducted exploratory interviews with students in ML/AI courses, revealing that students' perceptions of a career in these fields diverge based on their interest and programming confidence. Factors such as exposure to the field, interpretations of its boundaries, and beliefs about necessary skills influence students' intentions to persist. The study highlights the importance of social belonging and close mentorship in fostering persistence, suggesting avenues for future research focusing on these aspects, intersectional identity, and introductory courses. Complementing this focus on persistence, Chen (2022) emphasizes the critical role of mentorship in maintaining diversity within the AI community, particularly for underserved students. The study underscores the need for guidance in navigating the conference and publication process, especially given the rise of predatory conferences. The proposed PreDefense mentorship program aims to equip students with the skills to identify legitimate venues and prepare them for ethical and successful research careers.

Beyond AI-specific fields, the influence of related technologies like robotics extends to broader skill development. Flores et al. (2024) investigated the impact of robotics groups in higher education, finding that participation significantly improves transversal skills such as teamwork, creativity, and problem-solving. Students involved in robotics also reinforced their theoretical knowledge and increased their interest in research and academic commitment, demonstrating the potential of educational robotics to promote active and collaborative learning. This resonates with the findings of Verostek et al. (2023), who examined the process of joining research groups, a crucial step in graduate education. Their comparative case study revealed disparities in students' perceptions of finding an advisor and inequities in available resources, highlighting the need for consistent advising throughout undergraduate and graduate experiences.

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References:

1. Assylzhan, I. et al., 2023. Intelligent System for Assessing University Student Personality Development and Career Readiness. arXiv. Available at: http://arxiv.org/abs/2308.15620v1.
2. Bashiri, M. & Kowsari, K., 2024. Transformative Influence of LLM and AI Tools in Student Social Media Engagement: Analyzing Personalization, Communication Efficiency, and Collaborative Learning. arXiv. Available at: http://arxiv.org/abs/2407.15012v1.
3. Faruque, S., Khushbu, S. & Akter, S., 2024. Unlocking Futures: A Natural Language Driven Career Prediction System for Computer Science and Software Engineering Students. arXiv. Available at: http://arxiv.org/abs/2405.18139v1.
4. Hirabayashi, S. et al., 2024. Harvard Undergraduate Survey on Generative AI. arXiv. Available at: http://arxiv.org/abs/2406.00833v2.
5. Bai, S., Chen, W. & Gao, Z., 2024. Exploring the MBTI distribution among Chinese undergraduate physics students: the influence of family income on career trajectories. arXiv. Available at: http://arxiv.org/abs/2411.01379v1.
6. Eran-Jona, M. & Nir, Y., 2020. The academic career in physics as a "deal": Choosing physics within a gendered power structure and excellence as an extra hurdle for women. arXiv. Available at: http://arxiv.org/abs/2010.13115v1.
7. Wasil, A. et al., 2024. AI Emergency Preparedness: Examining the federal government's ability to detect and respond to AI-related national security threats. arXiv. Available at: http://arxiv.org/abs/2407.17347v2.
8. Flores, G. et al., 2024. De la Extensión a la Investigación: Como La Robótica Estimula el Interés Académico en Estudiantes de Grado. arXiv. Available at: http://arxiv.org/abs/2411.05011v1.
9. Mao, K. et al., 2023. "Just a little bit on the outside for the whole time": Social belonging confidence and the persistence of Machine Learning and Artificial Intelligence students. arXiv. Available at: http://arxiv.org/abs/2311.10745v1.
10. Chen, T., 2022. PreDefense: Defending Underserved AI Students and Researchers from Predatory Conferences. arXiv. Available at: http://arxiv.org/abs/2201.13268v1.
11. Verostek, M., Miller, C. & Zwickl, B., 2023. Inequities and misaligned expectations in PhD students' search for a research group. arXiv. Available at: http://arxiv.org/abs/2307.07008v1.
12. Wang, Y. et al., 2021. Seek for Success: A Visualization Approach for Understanding the Dynamics of Academic Careers. arXiv. Available at: http://arxiv.org/abs/2108.03381v2.

13. Souto-Maior, J. & Shroff, R., 2023. Differences in academic preparedness do not fully explain Black-White enrollment disparities in advanced high school coursework. arXiv. Available at: http://arxiv.org/abs/2306.15075v2.
14. Ellis, J., Fosdick, B. & Rasmussen, C., 2015. Women 1.5 Times More Likely to Leave STEM Pipeline After Calculus Compared to Men: Lack of Mathematical Confidence a Potential Culprit. arXiv. Available at: http://arxiv.org/abs/1510.07541v1.
15. Quinn, T. & Coghlan, S., 2021. Readying Medical Students for Medical AI: The Need to Embed AI Ethics Education. arXiv. Available at: http://arxiv.org/abs/2109.02866v1.
16. Katsamakas, E., Pavlov, O. & Saklad, R., 2024. Artificial intelligence and the transformation of higher education institutions. arXiv. Available at: http://arxiv.org/abs/2402.08143v1.
17. Capretz, L. et al., 2022. Social Aspects of Software Testing: Comparative Studies in Asia. arXiv. Available at: http://arxiv.org/abs/2205.07781v1.
18. Baucks, F. et al., 2024. Gaining Insights into Group-Level Course Difficulty via Differential Course Functioning. arXiv. Available at: http://arxiv.org/abs/2406.04348v1.
19. Rasnayaka, S. et al., 2024. An Empirical Study on Usage and Perceptions of LLMs in a Software Engineering Project. arXiv. Available at: http://arxiv.org/abs/2401.16186v1.
20. Burstein, D., Kenter, F. & Shi, F., 2018. Leveraging local network communities to predict academic performance. arXiv. Available at: http://arxiv.org/abs/1810.04730v1.
21. Barradell, S., 2022. Reimagining Preparedness of Health Professional Graduates Through Stewardship. Teaching and Learning in Medicine, 35(4), pp.486–495. Available at: https://doi.org/10.1080/10401334.2022.2148108.
22. Feder, J., 2019. As Industry Changes, So Does Petroleum Engineering Education. Journal of Petroleum Technology, 71(12), pp.44–48. Available at: https://doi.org/10.2118/1219-0044-jpt.