The Use of Gen-AI for Personalized Learning in Higher Education for Neurodiverse Learners: A Rapid Literature Review

Cheryl Burris

College of Education and Human Development, George Mason University

AIT 790: AI in Education

Dr. Aditya Johri

May 07, 2025

Abstract

AI technologies are increasingly recognized for their role in enhancing instructional design and personalizing learning in higher education. These technologies adapt content, assessments, and feedback to meet individual student needs. A review of twenty-five studies—including systematic reviews, empirical investigations, and literature syntheses—highlights various AI applications, such as adaptive learning systems, intelligent tutoring systems, and natural language processing tools. Many of these studies indicate that such approaches not only boost engagement but also improve academic performance, with one study reporting a notable 25% increase in test scores. Additionally, AI enhances accessibility through features like text-to-speech and voice recognition. Effective implementation of these technologies in higher education requires careful consideration of several factors: 1. Phased, user-centered integration of AI tools within existing Learning Management Systems; 2. Investment in robust IT infrastructure and comprehensive faculty training programs; and 3. A strong focus on ethical frameworks to ensure data protection, address algorithmic bias, and respect student autonomy. When institutional, technical, and ethical considerations are skillfully balanced, these measures can significantly enhance personalized learning support, particularly for neurodivergent learners and those with learning disabilities.

Keywords: AI, artificial intelligence, instructional design, higher education, personalized learning, neurodivergent

The Use of Gen-AI for Personalized Learning in Higher Education for Neurodiverse Learners: A Rapid Literature Review

In recent years, technological advances have surged with the rapid adoption of Generative Artificial Intelligence (Gen-AI). As a result, the promises of self-paced instruction, instant access to knowledge, and opportunities for personalized learning are now quickly becoming available. Despite this, some students still struggle in higher education because their challenges are not fully understood, considered, or accommodated in digital learning environments. (Green & Rabiner, 2012; Friedman & Nash-Luckenbach, 2024).

Defining the Neurodivergent Context

In 2024, Le Cunff, Giampietro, and Dommett released a systematic review that addressed essential questions regarding the relationship between cognitive load in online learning and neurodivergence. While noting that this is not entirely new, the authors revealed a concerning gap in the literature: out of the 90 studies conducted across 21 countries, a staggering 92% failed to consider neurodiversity as a potential factor affecting cognitive load in online learning (Le Cunff et al., 2024). Additionally, the emerging evidence indicated that individuals diagnosed with neurodivergence may demonstrate unique patterns of cognitive load when engaging in digital learning platforms (Le Cunff et al., 2024).

Their concerns about managing cognitive load and recognizing neurodiversity raise an important issue: the lack of neurodiverse representation in research studies. As Le Cunff et al. (2024) highlight, studies that include neurodivergent learners often rely on subjective measures for cognitive load, indicating a scarcity of objective assessments. Consequently, a gap in understanding exists regarding how cognitive load affects neurodiverse learners and how instructional design can be adapted to support them.

Additionally, researchers have proven there is a link between emotional cognitive load, well-being, and academic success (Asma & Dallel, 2020; Atiomo, 2020; Banu et al., 2021; Hamilton & Petty, 2023; Le Cunff et al., 2024; Taylor, 2023; Yu et al., 2018; Wheeler, 2024). Building on this, researchers have established the relationship between cognitive load and executive function management (Figueroa et al., 2017; Grosvenor, 2022; Jones et al., 2016; Meijs, 2021; Southon, 2022), self-regulation (Meijs et al., 2021; Ng et al., 2024), self-determination (Alamri et al., 2020; Oga-Baldwin, 2015), and self-directed learning (Adlinda & Mohib, 2020; Al Mamun et al., 2020). Furthermore, post-secondary education for neurodivergent learners faces significant gaps in learning theories (Friedman & Nash-Lukenback, 2023), pedagogical approaches (Hamilton & Petty, 2023), and accessibility, accommodations, and learner-centered scaffolding (Kelly, 2024; Doo et al., 2020).

Lack of Support in Higher Education

However, despite these research findings and their demonstrated interconnectedness, neurodiverse college students may encounter more challenges, lower motivation, and diminished success (DuPaul et al., 2019). Higher education may also neglect neurodivergent intelligences (Isacoff et al., 2022), leaving many neurodiverse learners feeling overwhelmed, under-supported, and forced to independently navigate the significant obstacles they frequently encounter during their studies (Azuka et al., 2024; Burgstahler, 2018; Hamilton & Petty, 2023; Kelly, 2024). As a result, despite the latest educational and technological advances, there is a need for a deeper understanding of the adult neurodivergent experience in higher education by the institutions, instructors, and instructional designers responsible for creating their learning environments. By collectively considering the difficulties that neurodiverse learners face due to their exclusion from assessment development, defined pedagogy, relevant instructional design theories, curriculum considerations, and scaffolding for digital learning environments, it may be time to determine whether higher education is prepared to adopt an AI-enabled heutagogical approach for cognitively accessible learning. To do so, it is essential to examine emerging literature to establish if educational technology has entered the third paradigm of AI in education, where AI empowers the personalization of learning while the learner retains agency over their learning (Ouyang & Jiao, 2021).

Potential for AI-Enabled Education

In recent conversations regarding the use of AI, Siemens et al. noted that "learning, sensemaking, and decision-making" (2022, p. 2) were the overlapping areas between artificial and human cognition. In this overlapping area, emerging research reveals that AI's transformative potential supports neurodivergent learners through personalized and strengths-based approaches to reduce cognitive load and enhance executive function (Researcher, 2025; Laudato & Zaugg, 2025). For neurodivergent learners in higher education, AI can benefit them in several ways (Burris, 2025): by creating accessible and equitable learning environments, eliminating barriers through supports provided by adaptive technologies, and offering responses and clarifications. Additionally, AI-assisted audio-learning modules have improved reading engagement and academic success by adapting content through multiple modalities (Jafarian & Kramer, 2025).

Researchers also emphasize that AI can effectively address skill gaps across various neurodevelopmental profiles. Iannone and Giasanti (2023) highlight that integrating machine learning with assistive technologies enhances social reciprocity for individuals with autism by examining real-time interactions. At the same time, natural language processing (NLP)-driven tools assist dyslexic students in interpreting complex texts through visual-spatial translations

("Using generative AI", n.d.). These approaches align with the framework presented by Mollick and Mollick (2023), which considers AI across seven different approaches (including Mentor, Coach, and Simulator) and focuses on the learner's metacognitive growth while avoiding excessive dependence on automated solutions.

Consequently, critical discussions arise regarding the ethical implementation of AI tools. While AI can empower learners with customizable support (Laudato & Zaugg, 2025), researchers caution against potential biases in diagnostic algorithms and stress the importance of including neurodiverse training datasets (Mishra, 2024). The U.S. Department of Education (2023) further underscores the need for "human-in-the-loop" systems that maintain learner autonomy while harnessing AI's adaptive features (Gibson, 2024). Overall, the literature highlights the potential for AI-enabled support and its possibility to effectively apply Universal Design for Learning (UDL) principles on a broad scale, provided that strict safeguards for privacy and security self-determination accompany implementations (Mollick & Mollick, 2023).

Research Aims and Questions

I aim to explore how AI can effectively support instructional design and personalized learning for neurodivergent learners in higher education. Research indicates that AI technologies can tailor content, assessments, and feedback according to the learner's needs (Herrería Gallardo et al., 2024). Therefore, the following research questions informed the literature search and synthesis:

RQ1: What evidence exists for AI's effectiveness in supporting neurodivergent learners in higher education?

RQ2: How robust is the emerging literature? What are the key findings, current gaps, and areas for future research?

Methods

I undertook a rapid review to explore my research questions. While a rapid literature review lacks a standard definition, it can be defined as an evolving knowledge synthesis method that omits or streamlines some aspects of the systematic review process to provide timely information (Smela et al., 2023; Tricco et al., 2015). There are three key features of this method: first, it typically requires only one reviewer; second, it is ideal for emerging research topics; and third, it has time and resource constraints. However, there is potential bias when using only one reviewer, since the reviewer performs both the study selection and data extraction roles. During the study selection, there is the potential for less transparency and reproducibility. With the role of data extraction, there is the potential for increased errors. Regardless, the decision to act as the only reviewer was a pragmatic one, given the lack of availability of peers and the limitation of time and resources.

Search Strategy

I conducted a systematic literature search in the following databases: ACM Digital Library, PubMed, Google Scholar, Scopus, Semantic Scholar, ERIC, EBSCOhost, PsycINFO, Web of Science Core Collection, Academic Search Premier, and IEEE Xplore Digital Library. I used this exact keyword string for all database searches: "AI OR Artificial Intelligence AND Instructional Design AND Higher Education OR University OR College AND Personalized Learning OR Adaptive Learning AND Neurodiv* OR Inclusive". This was an attempt to ensure I obtained consistent results. The searches were limited to peer-reviewed journals, high-quality conference proceedings, and grey literature.

I conducted my initial search in March 2025. At first, I limited it to only 2025 publications. However, with this strategy, I found only two journal articles that suited my needs.

Consequently, I conducted a second search in April 2025, expanding my search period from January 2024 to April 2025. Ultimately, I decided against conducting additional manual searches for relevant articles due to time constraints.

Eligibility Criteria and Review Selection

To be eligible for the review, I selected publications that met the following inclusion and exclusion criteria. My inclusion criteria consisted of peer-reviewed journal articles, high-quality conference proceedings, or grey literature published since January 2025; articles written in English or accompanied by an English translation; and those that focused on the integration of AI in education, neurodivergent learners, higher education settings, personalized learning approaches, and ethical/privacy issues. My exclusion criteria included studies that concentrated solely on K-12, non-English papers without a translation, those without available abstracts, and articles for which the full text was inaccessible. For the publications I retrieved, I performed four rounds of selection. First, I reviewed all titles and keywords. Second, I examined only the abstracts. Third, I conducted an eligibility screening and set aside any article for which I questioned its eligibility based on the inclusion criteria. Finally, I reviewed articles from my "not easy to determine" stack for the final record selections to be included in the review.

Critical Appraisal

Once I had my list of selected publications, I screened them to ensure they were appropriate for my review. I screened for population, interventions, design, outcomes, and discussions regarding privacy or ethical concerns (see Table 1). This table presents the screening criteria and question strategy for each criterion. *Population* and *Intervention*s were divided into two subsections. I considered the questions holistically when I appraised its value and judged its appropriateness to be screened into my review.

Table 1: Eligibility Screening Criteria

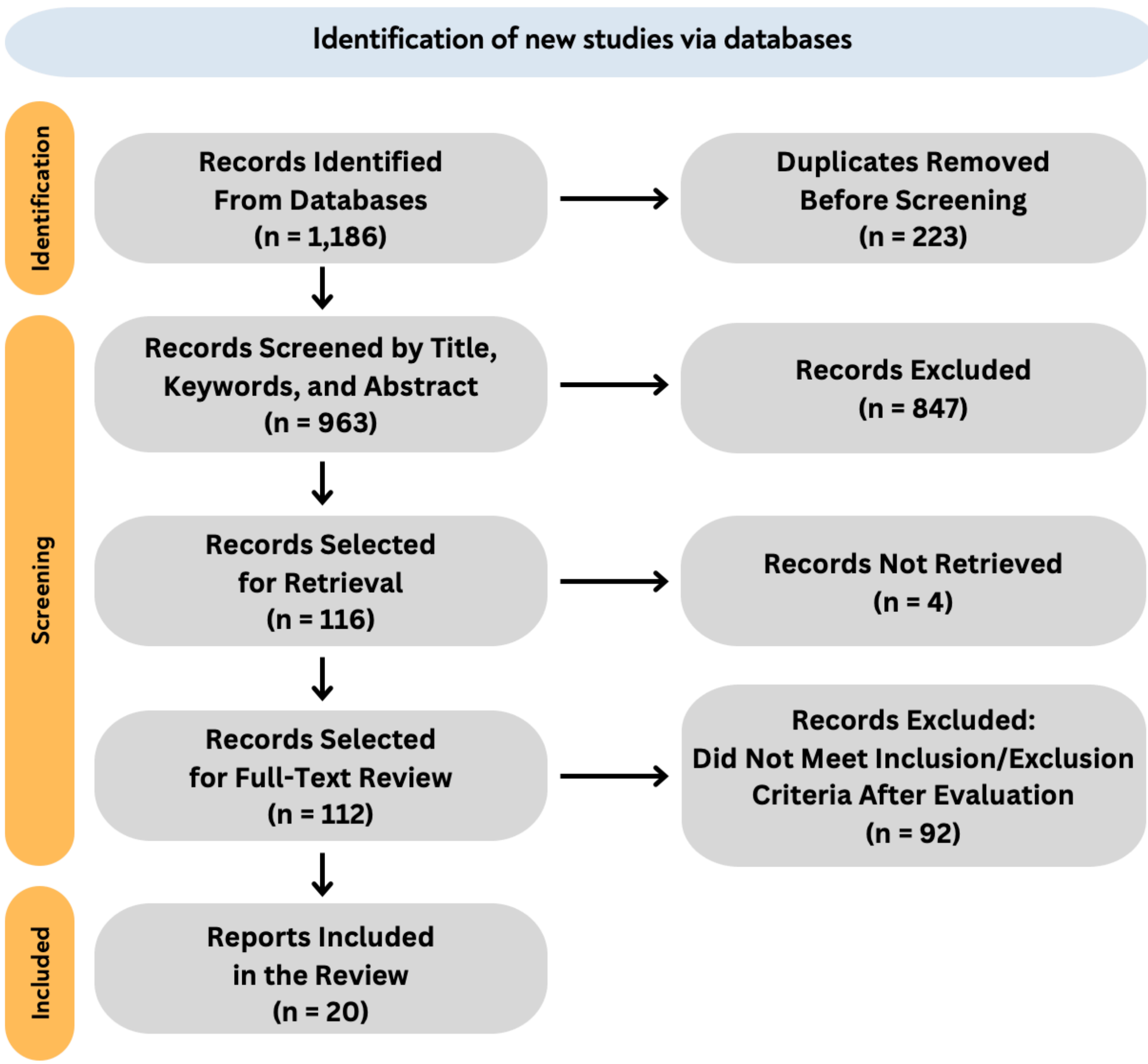
Criteria	Questioning Strategy
Population – Setting	Was the study conducted in a higher education setting (university, college, community college, or post-secondary institution)?
Population – Participants	Did the study include neurodivergent learners or students with learning disabilities as primary participants?
Intervention Technology	Did the study implement AI-based or machine learning tools / systems for an educational purpose?
Intervention Approach	Did the study focus on personalized learning or individualized instructional approaches?
Study Design	Is this an empirical study (qualitative, quantitative, or mixed-methods), systematic review, or meta-analysis?
Outcomes	Did the study report measurable outcomes related to learning, student engagement, or intervention effectiveness?
Privacy / Ethical Considerations	Did the study address privacy considerations in the implementation of the AI-based intervention?

Results

Description of Included Publications

Database searches identified 1,186 records, with 223 removed due to duplication. Then, 963 records were screened by title, keywords, and abstract, with 847 records excluded. Of the remaining 116 records selected to be retrieved, four were unavailable. Of the remaining records, 112 were selected for full-text review. After a detailed review, 92 records were excluded since they did not meet the inclusion/exclusion criteria, and 20 records were included in this review. Figure 1 presents the screening process in the Preferred Reporting Items for Systematic review and Meta-Analysis (PRISMA) flow diagram (Page et al., 2021).

Figure 1: PRISMA Flow Diagram



Data Extraction Process

I summarized the 20 records in Table 1, Characteristics of Included Studies, which can be found in Appendix A. This table provides an overview of the 20 studies by highlighting four key areas: Study Type, Focus Area, Population Studied, and Implementation Context. First, I classified the study designs by identifying explicit methodological descriptions in the column and categorizing them as systematic reviews, exploratory reviews, empirical studies (quantitative, qualitative, or mixed-methods), or theoretical analyses. These results can be found in the second column, Study Type (see Appendix A). Then, I focused on gathering any information that described the research methodology, the AI-enabled intervention, and any personalized learning approaches. These annotations can be found in the third column, Focus Area. The fourth column, Population Studied, noted the participants and any relevant information such as neurodivergent labeling or student demographics. The final column, Implementation Context, lists the specific context for the study with provided details.

Quality Appraisal of Characteristics

Upon reviewing the information categorized under Study Types, I found 10 systematic reviews, five empirical studies, three literature reviews, and two scoping reviews. After examining the information related to Focus Types, I discovered six studies focusing on personalized learning, five on inclusive education, four on learning disabilities, and five on specific use cases (such as with an LMS). When investigating the Population Studied, I found seven studies specifying higher education students, eight studies mentioning learning disabilities, one study noting a diverse student selection, one study focusing on K-12 in addition to higher education, and three studies that did not specify their population. Finally, after reviewing the Implementation Context, I found that eight studies took place at a higher education institution, one applied to K-12 in addition to higher education, and 11 studies did not reference their specific educational context.

Synthesis

AI technology is playing an increasingly vital role in enhancing educational interventions, particularly for neurodivergent learners. A range of AI tools and technologies has been developed specifically to support this goal, focusing on adaptive learning and personalized assistance tailored to the unique needs of each student. Key features within these AI systems facilitate a more inclusive learning environment, ensuring that neurodivergent learners receive the specialized support they need to succeed.

To foster a personalized learning experience, various strategies are implemented that leverage the capabilities of AI. This technology enables personalized learning by adjusting educational content and approaches based on each learner's distinct strengths and challenges. For neurodivergent students, such adaptations might include customized pacing, alternative assessment methods, and resources tailored to their learning preferences. Through these individualized educational support mechanisms, AI empowers learners by creating a responsive and nurturing academic atmosphere.

The integration of AI technologies in education has yielded several significant findings and outcomes. Research shows that these interventions enhance learning effectiveness, as students respond positively to tailored instruction. Furthermore, student engagement often improves, with learners displaying increased motivation and active participation in their studies. Accessibility improvements represent another key outcome, as AI technologies help to bridge gaps in educational resources, providing neurodivergent students with opportunities to thrive.

Overall, the experiences of neurodivergent learners reflect a more inclusive and enriching educational journey, made possible by the application of AI tools.

Nevertheless, ethical considerations must also be prioritized in the use of these technologies. Ensuring privacy protection mechanisms is crucial to safeguarding student information, while attention to algorithmic bias is necessary to promote fairness in learning opportunities. Preserving learner autonomy is equally important, allowing students to maintain control over their educational paths. Additionally, ongoing efforts must address challenges related to accessibility and inclusivity to ensure that all learners can fully benefit from these innovative advancements in education.

Findings

AI-Enabled Personalization Strategies

Key Themes

Based on the insights gathered from the reviewed studies, several key themes emerged regarding AI-enabled personalization strategies in education. I summarized these findings in Table 2, AI-Enabled Personalization Strategies, located in Appendix B. This table lists each study and the strategies it presents for AI-enabled personalization.

Technology Types. First, a diverse range of technologies was highlighted. Adaptive learning systems and platforms were discussed in three studies, while six studies focused specifically on AI-based systems and tools. Additionally, intelligent tutoring systems were covered in three studies, and machine learning and natural language processing were explored in two studies each.

Personalization Methods. When it came to personalization methods, adapting or tailoring content to individual needs stood out as the most common approach, appearing in ten studies. Two studies highlighted the creation of personalized learning paths, and three examined adaptive assessments. Other notable methods included real-time adaptive support, cognitive scaffolding, and sentiment analysis, showcasing the varied strategies for enhancing learning experiences.

Learning Contexts. The contexts in which these personalization strategies were applied also varied significantly. Six studies concentrated on higher education, with additional research focusing on graduate-level education, K-12 environments, engineering courses, and broader educational institutions.

Accessibility Features. Furthermore, the studies emphasized the importance of accessibility features. Voice-related technologies and reading assistants or text-to-speech applications were noted in two studies each. Other important accessibility considerations included adaptations to user interfaces and user experiences, discussed in one study, as well as the application of Universal Design for Learning principles, image recognition, and learning management system integration, each appearing in individual studies.

Together, these themes illustrate a comprehensive landscape of AI-enabled personalization strategies, reflecting a commitment to enhancing educational experiences across various settings and for diverse learners.

Implementation and Integration

The integration of AI technologies in higher education, particularly for neurodivergent learners, is a complex process that encompasses several critical factors.

Institutional Adoption Patterns. One of the primary themes that emerged is the varied patterns of institutional adoption. Many educational institutions are opting for a gradual approach, initiating their efforts with pilot programs or specific courses before expanding to a broader rollout. This rate of AI adoption significantly differs from one institution to another, influenced by factors such as technological readiness, faculty expertise, and institutional priorities. Successful integration often flourishes through interdisciplinary collaboration, with key players from education departments, IT services, and accessibility offices working together.

Technical Infrastructure Requirements. Another crucial element is the technical infrastructure necessary for effective implementation. Institutions must ensure they have robust IT systems, encompassing the necessary hardware and software to support AI-powered learning environments. Proper data management is also vital, given the sensitive nature of student information; secure storage, processing, and careful handling are essential. Moreover, it is important for AI tools to integrate seamlessly with existing Learning Management Systems, enhancing the overall user experience, while also ensuring that the infrastructure supports a range of accessibility features, such as screen readers and voice recognition software.

Faculty Training and Support. Faculty training and ongoing support are pivotal in this process. Comprehensive professional development programs are essential for helping faculty understand and effectively leverage AI tools. Continuous technical and pedagogical support can greatly enhance the successful integration of these technologies. Addressing faculty resistance is also critical; it involves educating staff about the potential of AI and showcasing its benefits. Furthermore, training on ethical considerations, including data privacy and algorithmic bias, is necessary to equip faculty for responsible usage.

Challenges in Implementation. Despite these efforts, the path to implementing AI technologies is fraught with challenges. Institutions often encounter technical difficulties, including system compatibility issues, concerns about data quality, and questions regarding the reliability of AI algorithms. Ethical dilemmas, such as privacy protection, algorithmic bias, and the need to maintain learner autonomy, are significant hurdles as well. Resource constraints, particularly the high costs associated with AI technologies and the necessity for specialized expertise, can further complicate adoption attempts. Additionally, addressing accessibility gaps remains a persistent issue; ensuring that AI systems are fully accessible to all students, including those with disabilities, is essential.

Successful Integration Strategies. To foster successful integration, several effective strategies can be adopted. A user-centered design approach that actively involves students—especially neurodivergent learners—in the design and implementation processes can lead to more effective and accessible systems. An adaptive implementation strategy that embraces flexibility and allows for adjustments based on user feedback and evolving needs is also crucial. Moreover, a holistic approach that includes not just technological changes but also necessary shifts in pedagogical methods and institutional policies can enhance integration efforts. Finally, establishing and adhering to clear ethical frameworks is essential for ensuring the responsible use of AI in education.

Educational Outcomes and Effectiveness

Key Themes

Based on the insights gathered from the reviewed studies, several key themes related to educational outcomes and effectiveness have emerged. I summarized these findings in Table 3, Educational Outcomes and Effectiveness, which can be found in Appendix 3. This table presents the interventions, the resulting outcomes, and the success factors and limitations mentioned in the study.

Various intervention types were highlighted, particularly AI personalized and adaptive learning, which featured prominently in ten studies. Other notable approaches included the use of

AI tailored for specific learning needs, strategies for inclusive education, AI-mediated discussions, and the integration of AI with a range of educational technologies.

The measured outcomes from these interventions were generally positive. Engagement levels improved, as reported in ten studies, while seven studies indicated enhancements in performance or overall learning outcomes. Additionally, five studies demonstrated the benefits of personalized learning and support. Furthermore, other outcomes included increased motivation, improved academic performance, and specific advancements in skills such as reading, math, and cognitive capabilities.

Success in these interventions can largely be attributed to several critical factors. Personalization emerged as a significant theme, with eight studies emphasizing the importance of tailored feedback, experiences, and content. Furthermore, two studies noted adaptive content and early interventions as vital elements. Other influential factors included the delivery of real-time support, customized instruction, the use of culturally relevant tools, and the incorporation of gamification elements.

Nevertheless, the studies also pointed out several limitations that must be addressed. Two studies raised concerns about potential biases in AI algorithms and data privacy issues. Additional limitations included small sample sizes, a lack of extensive empirical evidence, challenges in implementation, and various ethical considerations.

Limitations and Areas of Concern

Lack of Empirical Evidence. Many studies examining AI interventions in education face criticism due to their lack of empirical evidence, often relying on theoretical frameworks or limited data sets. This underscores the pressing need for more robust, large-scale empirical research to substantiate the findings presented.

Variability of Measured Outcomes. The outcomes measured across different studies vary considerably, making direct comparisons challenging. Standardized measures of effectiveness would be highly beneficial to enhance the reliability of future research.

Potential Bias. Some studies also raise concerns about potential biases, particularly algorithmic bias. This highlights the need for careful implementation of AI tools to ensure equity in educational contexts.

Privacy and Ethical Concerns. Numerous studies raise important issues related to privacy and ethics, indicating that these areas require vigilance in any research involving AI.

Limited Long-term Data. Another significant limitation is that most studies focus primarily on short-term outcomes, creating a noticeable gap in research regarding long-term effects. There is a clear need for longitudinal studies that investigate the sustained impact of AI interventions on learning and academic success.

Context Specificity. Finally, it is essential to recognize that the effectiveness of these interventions may vary significantly depending on specific contexts, subject areas, and student populations. This reinforces the importance of further research to understand these contextual factors, as they play a crucial role in determining the success of AI in educational settings.

Privacy and Ethical Considerations

The integration of AI technologies in higher education, especially in support of neurodivergent learners, brings forth a host of significant privacy and ethical considerations.

Data Protection Measures. A pivotal aspect of this discussion revolves around data protection measures. Research underscores the necessity of encrypting student data and employing anonymization techniques to safeguard individual privacy. Additionally, it is crucial for educational institutions to focus on collecting only essential data, such as computed metrics rather than raw content, to minimize potential privacy risks. Effective data storage and management systems are also vital for preventing unauthorized access and protecting against data breaches.

Ethical Implementation Frameworks. Establishing robust ethical implementation frameworks is essential. Transparency in AI algorithms and the associated decision-making processes emerge as fundamental themes within the literature. Addressing algorithmic bias and ensuring fair treatment of all students, particularly those from underrepresented groups or with disabilities, remains a pressing concern. It is crucial to delineate clear lines of responsibility and accountability for AI decisions in educational contexts. Many studies advocate for developing comprehensive ethical guidelines tailored specifically to the use of AI in education.

Student Rights and Consent. In terms of student rights and consent, obtaining informed consent from students or their guardians for data collection and AI-driven interventions is paramount. Some studies suggest that students should have the right to opt out of AI systems without facing educational disadvantages. Furthermore, clarifying the issues surrounding data ownership and students' rights concerning their educational data is becoming an increasingly important concern.

Specific Ethical Challenges. The ethical challenges in this realm are multifaceted. A significant dilemma lies in balancing the advantages of AI-driven personalization with the necessity of preserving learner autonomy and decision-making skills. Experts caution against an overreliance on AI systems, as this could jeopardize critical thinking skills and diminish valuable human-to-human interactions in educational settings. Additionally, ensuring equitable access to AI technologies and addressing the potential exacerbation of existing educational inequalities is a vital ethical consideration that cannot be overlooked.

Privacy and Accessibility Trade-offs. Navigating the tension between protecting privacy and fulfilling the data needs for effective personalization poses another ongoing challenge. It is critical to strike a careful balance when allowing AI-driven support for neurodivergent learners while safeguarding their privacy. There are also specific considerations related to neurodiversity; researchers emphasize the importance of involving neurodivergent individuals in developing and testing AI systems to ensure their unique needs are met. Caution must be exercised to prevent the inadvertent stigmatization or marginalization of neurodivergent learners within these systems.

Ongoing Monitoring and Evaluation. Lastly, continuous monitoring and evaluation of AI systems are crucial in identifying and addressing emerging ethical issues. As AI technologies evolve, ethical frameworks and guidelines must be regularly updated to address new challenges and ensure that they remain relevant in an ever-changing educational landscape.

These themes offer valuable insights into the privacy and ethical considerations of using AI in higher education for neurodivergent learners. However, it is important to recognize that many studies fail to provide detailed and practical solutions to these challenges. There is a pressing need for further research and the development of practical guidelines for implementing ethical AI systems in educational contexts, especially to support neurodivergent learners effectively.

Discussion

Effectiveness of AI to Offer Support

Research on the role of artificial intelligence in supporting neurodivergent learners in higher education reveals a variety of effective interventions. One key strategy is the use of personalized and adaptive learning methods, which specifically cater to the diverse needs of individual learners. AI plays a pivotal role in promoting inclusive education by facilitating meaningful, AI-mediated discussions and providing targeted AI tutoring that enhances the overall learning experience. Additionally, integrating AI with other technologies helps create a more cohesive educational environment.

The outcomes of these interventions are significant, showcasing considerable improvements in several areas. Students often exhibit enhanced engagement, better academic performance, and improved learning outcomes. Moreover, the motivation levels and cognitive capabilities of neurodivergent learners can show marked advancements, highlighting the critical role AI plays in fostering personalized learning experiences.

Looking ahead, several considerations will further optimize the use of AI in education. Personalizing feedback, experiences, and content will be essential, as will the development of adaptive materials that resonate with individual learning styles. Early interventions and on-demand support can provide timely assistance, while incorporating elements such as gamification and culturally relevant tools will make the learning process more engaging. Ultimately, tailored instruction will be crucial in maximizing the effectiveness of AI to meet the unique needs of neurodivergent learners, ensuring they thrive in their educational journeys.

Robustness of Emerging Literature

The emerging literature on the application of AI in personalized learning highlights both significant opportunities and essential needs. One of the most compelling advantages of using AI is its capacity to harness data mining techniques, which can optimize learning processes and greatly enhance the educational experience. Intelligent Tutoring Systems (ITS) play a pivotal role in this arena, enabling dynamic adjustments that tailor learning to individual needs and fostering responsive educational environments.

However, to fully leverage these benefits, there is an urgent need for training that equips educators with technological skills and pedagogical expertise. Additionally, promoting AI literacy among educators and students is crucial for successful integration into the classroom.

When we look at the potential benefits for neurodivergent learners, AI holds the promise of creating more accessible and equitable learning environments. By utilizing adaptive technologies, AI can effectively remove barriers to learning, providing immediate feedback and clarification that support these learners in their educational journeys. That said, it is important to address the risk of algorithmic bias, especially considering that neurodivergent populations can often be viewed as statistical outliers.

In higher education, the landscape is evolving, with many universities actively implementing AI technologies and a burgeoning interest in research on the subject. Nonetheless, there remains a significant gap in the use of AI for instructional design that needs to be explored further. Furthermore, it is critical to tackle pressing issues such as privacy concerns and to ensure that human interactions remain a vital component of the learning process, helping to prevent feelings of isolation among students.

Implementation

Gaps

Several notable gaps need to be addressed. First, there is a significant lack of empirical evidence, which undermines the foundation of many claims and strategies. Additionally, accessibility remains a critical issue, as not everyone has equal opportunities to participate or benefit from available resources.

Moreover, the roles of faculty members need to be clearly defined and supported to ensure effective engagement in these initiatives. Finally, better alignment with formal frameworks is necessary, as this would help establish a coherent structure and facilitate integration within existing systems. Addressing these gaps is essential for fostering a more inclusive and effective environment.

Limitations

When examining this topic, it is important to recognize several key limitations. One notable issue was the significant variability across studies, which can lead to inconsistent findings and interpretations. Additionally, potential bias and discrimination may have affected results, skewing the outcomes in ways that compromise validity. Privacy and ethical concerns are also paramount; protecting sensitive information is vital in any research endeavor. Furthermore, the context in which the research takes place can significantly influence its applicability, as findings may not be universally relevant. Technical challenges may complicate the data collection and analysis processes, making it difficult to achieve reliable results. Lastly, resource constraints can limit a study's depth and breadth, often hindering the robustness of its conclusions.

Ethical Considerations and Challenges

Several key factors emerge as vital when addressing ethical considerations and challenges in educational settings. First, data privacy safeguarding is paramount, ensuring that sensitive student information remains protected from unauthorized access. This leads to important questions about data ownership, who has the rights to student data, and how it should be appropriately utilized. Informed consent is another critical element, highlighting the necessity for learners to fully understand and agree to the terms under which their data will be shared and used. This concept also connects to learner autonomy, which emphasizes empowering students to take charge of their educational experiences and make informed decisions about their learning.

Representation of neurodivergent individuals within the broader spectrum of neurodiversity is essential, ensuring that diverse perspectives and needs are addressed. Equally important is the mitigation of algorithmic bias, which can produce unequal outcomes in educational technologies and may inadvertently reinforce existing inequalities.

Transparency in processes plays a crucial role in building trust among all stakeholders, as it allows teachers and learners to understand how decisions are made in digital learning environments. However, the increasing reliance on technology can lead to a reduction in human interaction, which may negatively impact the essential relationships that support effective learning.

The preparation and competency of teachers are also vital in navigating these ethical challenges, ensuring that educators possess the skills needed to manage both technological tools and ethical considerations. Finally, the reliability of content and responses generated by educational tools is critical, as students depend on these resources for accurate information and guidance.

Despite the growing recognition of these ethical challenges, many articles often lack practical solutions, leaving educators and institutions without clear, actionable strategies to address them effectively.

Engagement Strategies

To enhance engagement in learning environments, a variety of effective strategies can be employed. One key approach is the use of personalized learning experiences, where AI serves as an executive assistant, course designer, and course manager. This enables the creation of tailored educational pathways that cater to individual needs and preferences, ensuring a more meaningful learning journey. In addition, integrating interactive and adaptable content can significantly enrich the educational experience. Techniques such as contextual learning, gamification, and timely feedback create dynamic opportunities that resonate with learners, making the material more engaging and relevant.

Social support and collaboration play an important role as well. By utilizing AI-assisted communication tools, learners can easily collaborate and customize their learning experiences, fostering a strong sense of community among peers. Furthermore, accessibility and accommodations must be prioritized to ensure that the learning environment is friendly and accommodating for everyone, particularly those with sensory and cognitive challenges. Lastly, engaging learners through participatory design and co-creation is vital. This strategy ensures that diverse voices are represented and that the content is applicable to real-life situations, leading to deeper engagement and a stronger investment in the learning process. Together, these strategies create a comprehensive framework that can transform the educational landscape, making it more inclusive and effective for all learners.

Strategies for Future Success

To foster future success, it is essential to embrace a user-centered design that prioritizes the involvement of neurodiverse learners from the very beginning and continuously throughout the process. Additionally, employing an adaptive implementation strategy allows for tailored responses that cater to the unique needs of each individual user. A holistic approach is also vital, as it integrates technological, institutional, and pedagogical elements to create a comprehensive learning environment. Finally, it is crucial to establish a strong ethical framework, ensuring that all practices are clear and consistently adhered to in order to support these initiatives effectively.

Future Research

Several key areas for future research stand out in higher education, particularly when it comes to neurodivergent learners. One important focus is the development of AI-enabled course designs specifically tailored to enhance the educational experience for these learners. Such innovative approaches can help cater to their unique needs and learning styles.

Equally vital is the preparation and development of teachers. Equipping educators with the right tools and strategies is crucial for effectively supporting neurodivergent students in their learning journeys. Additionally, exploring personalized learning models that address the distinct challenges faced by neurodivergent individuals can further improve educational outcomes. This could involve implementing adaptive algorithms capable of accommodating various learning profiles, ensuring that each student receives the unique support they require.

Finally, promoting AI literacy among both learners and educators enhances their ability to navigate and effectively utilize technology within educational settings. Finally, establishing ethical frameworks is critical to protect disadvantaged populations and ensure that advancements in educational technology do not inadvertently widen existing disparities. By concentrating on these aspects, we can work toward creating a more inclusive and supportive educational environment for all learners.

Conclusion

AI-enabled personalized learning in higher education holds great promise for both neurodivergent and neurotypical learners. Given the rapid development and integration of AI, it is both critical and in the best interest of the learners, educators, and institutions to approach the use of AI for neurodivergent learners with a sense of balanced integration (a human-in-the-loop instead of out-of-the-loop human...if you will), inclusive design to facilitate academic alignment with lived experiences, and pedagogical and policy advocacy to manage debate, navigate the challenges, and attend to gaps.

References

Adinda, D., & Mohib, N. (2020). Teaching and instructional design approaches to enhance students' self-directed learning in blended learning environments. *Electronic Journal of eLearning, 18*(2), 162-174. https://doi.org/10.34190/EJEL.20.18.2.005

Alamri, H., Lowell, V., Watson, W., & Watson, S. L. (2020). Using personalized learning as an instructional approach to motivate learners in online higher education: Learner self-determination and intrinsic motivation. *Journal of Research on Technology in Education, 52*(3), 322-352. https://doi.org/10.1080/15391523.2020.1728449

Al Mamun, M. A., Lawrie, G., & Wright, T. (2020). Instructional design of scaffolded online learning modules for self-directed and inquiry-based learning environments. *Computers & Education, 144*, 103695. https://doi.org/10.1016/j.compedu.2019.103695

Asma, H. & Dallel, S. (2020). Cognitive load theory and its relation to instructional design: Perspectives of some Algerian university teachers of English. *Arab World English Journal (AWEJ), 11*(4), 110-127. https://dx.doi.org/10.24093/awej/vol11no4.8

Atiomo, W. (2020). Emotional well-being, cognitive load and academic attainment. *MedEdPublish, 9*(1), 118. https://doi.org/10.15694/mep.2020.000118.1

Alkhawaldeh, M. A. & Khasawneh, M. A. (2023). Harnessing the power of artificial intelligence for personalized assistive technology in learning disabilities. *Journal of Southwest Jiaotong University, 58*(4). https://doi.org/10.35741/issn.0258-2724.58.4.60

Alotaibi, N. S. (2024). The impact of AI and LMS integration on the future of higher Education: Opportunities, challenges, and Strategies for transformation. *Sustainability, 16*(23), 10357. Strategies for Transformation. Sustainability 2024, 16, 10357. https://doi.org/10.3390/su162310357

Anuyahong, B., Rattanapong, C., & Patcha, I. (2023). Analyzing the impact of artificial intelligence in personalized learning and adaptive assessment in higher education. *International Journal of Research and Scientific Innovation, 10*(4), 88–93. https://doi.org/10.51244/ijrsi.2023.10412

Azuka, C. V., Wei, C. R., Ikechukwu, U. L., & Nwachukwu, E. L. (2024). Inclusive instructional design for neurodiverse learners. *Basic and Applied Education Research Journal, 5*(2), 59-67. https://doi.org/10.46303/cuper.2024.4

Banu, R., Al Siyabi, W. S. A., & Al Minje, Y. (2021, August). A conceptual review on integration of cognitive load theory and human-computer interaction. In 2021 International Conference on Software Engineering & Computer Systems and 4th International Conference on Computational Science and Information Management (ICSECS-ICOCSIM) (pp. 667-672). IEEE. http://doi.org/10.1109/ICSECS52883.2021.00127

Burgstahler, S. (2018). Inclusive online science education: What teachers need to know. In *Towards Inclusion of All Learners through Science Teacher Education* (pp. 115-123). Brill. https://doi.org/10.1163/9789004368422_013

Burris, C. (2025). Exploring the challenges of digital learning environments: Perspectives of neurodivergent learners in higher education. George Mason University.

Chalkiadakis, A., Seremetaki, A., Kanellou, A., Kallishi, M., Morfopoulou, A., Moraitaki, M., & Mastrokoukou, S. (2024). Impact of artificial intelligence and virtual reality on educational inclusion: A systematic review of technologies supporting students with disabilities. *Education Sciences, 14*(11), 1223. https://doi.org/10.3390/educsci14111223

Doo, M.Y., Bonk, C. J., & Heo, H. (2020). A meta-analysis of scaffolding effects in online learning in higher education. *International Review of Research in Open and Distributed Learning 21*(3), 60-80. https://files.eric.ed.gov/fulltext/EJ1267049.pdf

DuPau, G. J., Franklin, M. K., Pollack, B. L., Stack, K. S., Jaffe, A. R., Gormley, M. J., Anastopoulos, A. D., & Weyandt, L. L. (2018). Predictors and trajectories of educational functioning in college students with and without attention-deficit/hyperactivity disorder. *Journal of Postsecondary Education and Disability, 31*(2), 161–178. https://www.ncbi.nlm. nih.gov/pmc/articles/PMC6586431

Ejjami, R. (2024). The adaptive personalization theory of learning: Revolutionizing education with AI. *Journal of Next-Generation Research 5.0, 1*(1). https://doi.org/10.70792/jngr5.0.v1i1.8

El Naggar, A., Gaad, E., & Inocencio, S. A. M. (2024). Enhancing inclusive education in the UAE: Integrating AI for diverse learning needs. *Research in Developmental Disabilities, 147*, 104685. https://doi.org/10.1016/j.ridd.2024.104685

Faruqui, S. H. A., Tasnim, N., Basith, I., Obeidat, S., & Yildiz, F. (2024). Board 46: Integrating AI in higher education protocol for a pilot study with "SAMCares: An adaptive learning hub." *2024 ASEE Annual Conference & Exposition Proceedings*. https://doi.org /10.18260/1-2--47042

Figueroa, A. M., & Juárez-Ramírez, R. (2017). The problem of cognitive load in GUI's: Towards establishing the relationship between cognitive load and our executive functions. *2017 IEEE 41st Annual Computer Software and Applications Conference (COMPSAC),* 561-565. https://ieeexplore.ieee.org/document/8029990

Friedman, Z.L., & Nash-Luckenbach, D. (2024). Has the time come for Heutagogy? Supporting neurodivergent learners in higher education. *Higher Education 87*, 1905–1920. https://doi.org/10.1007/s10734-023-01097-7

Gibson, R. (2024, September 10). The impact of AI in advancing accessibility for learners with disabilities. *EDUCAUSE Review*. https://er.educause.edu/articles/2024/9/the-impact-of-aiin-advancing-accessibility-for-learners-with-disabilities

Green, A. L. & Rabiner, D. L. (2012) What do we really know about ADHD in college students? *Neurotherapeutics, 9*(3), 559-568. https://www.sciencedirect.com/science/article/pii/S1878747923017300

Grosvenor, M. (2022). Strengthening executive function and self-regulation in early childhood classrooms. https://acf.gov/sites/default/files/documents/opre/efmapping_report_101416_final_508.pdf

Gupta, T. (2024). Adaptive learning systems: Harnessing AI to personalize educational outcomes. *International Journal for Research in Applied Science and Engineering Technology, 12*(11), 458–464. https://doi.org/10.22214/ijraset.2024.65088

Halkiopoulos, C. & Gkintoni, E. (2024). Leveraging AI in e-Learning: Personalized learning and adaptive assessment through cognitive neuropsychology—A systematic analysis. *Electronics, 13*, 3762. https://doi.org/10.3390/electronics 13183762

Hamilton, L. G. & Petty, S. (2023). Compassionate pedagogy for neurodiversity in higher education: A conceptual analysis. *Frontiers in Psychology, 14*. 1-9. https://doi.org/10.3389/fpsyg.2023.1093290

Herrería Gallardo, K. R., Ochoa Ordóñez, B. R., Alvarez Vinces, L. A., & Gallardo Ledesma, D. (2024). Integración de tecnologías de IA en estrategias de enseñanza inclusiva en instituciones de educación superior. Reincisol., 3(5), 1747–1760.

https://doi.org/10.59282/reincisol.v3(5)1747-1760

Hyatt, S. E., & Owenz, M. B. (2024). Using universal design for learning and artificial intelligence to support students with disabilities. *College Teaching*. 1-8. https://doi.org/10.1080 /87567555.2024.2313468

Iannone, A., & Giansanti, D. (2023). Breaking barriers—The intersection of AI and assistive technology in autism care: A narrative review. *Journal of Personalized Medicine, 14*(1), 41. https://doi.org/10.3390/jpm14010041

Isacoff, N. M., Le Cunff, A.-L., & Varma, V. (2022). *Neurodiverse Intelligences: Mapping the Multidimensional Construct of Neurodiversity*. Abstract from Diverse Intelligence Summer Institute, St Andrews, United Kingdom. https://kclpure.kcl.ac.uk/ws/portalfiles/portal/321058725/disi-2022-42y7si89ahu.pdf

Jafarian, N. R., & Kramer, A. W. (2025) AI-assisted audio-learning improves academic achievement through motivation and reading engagement. *Computers and Education: Artificial Intelligence, 8*, 100357. https://doi.org/10.1016/j.caeai.2024.100357

Jiali, S. (2024). The impact of artificial intelligence on personalized learning in education: A systematic review. *Pakistan Journal of Life and Social Sciences, 22*(2). https://doi.org /10.57239/pjlss-202422.2.00560

Jones, S. M., Bailey, R., Barnes, S. P., & Partee, A. (2016). Executive function mapping project: Untangling the terms and skills related to executive function and self-regulation in early childhood (OPRE Report No. 2016-88). Office of Planning, Research and Evaluation, Administration for Children and Families, U.S. Department of Health and Human Services. https://acf.gov/sites/default/files/documents/opre/efmapping_report_101416 _final_508.pdf

Khan, M. A., Khojah, M., & Vivek. (2022). Artificial Intelligence and Big Data: The Advent of New Pedagogy in the Adaptive E-Learning System in the Higher Educational Institutions of Saudi Arabia. *Education Research International, 2022*(1), 1263555. https://doi.org/10.1155/2022%2F1263555

Kelly, K. (2024). Building scaffolding instead of barriers: Accessibility for neurodivergent law student [Manuscript submitted for publication]. Moritz College of Law, The Ohio State University. http://dx.doi.org/10.2139/ssrn.4958152

Khanal, S., & Pokhrel, S. R. (2024). Analysis, modeling and design of personalized digital learning environment. arXiv preprint arXiv:2405.10476. https://doi.org/10.48550/arXiv.2405.10476

Laudato, M & Zaugg, T. (2025, February 27). Tech InCITIES: AI & inclusive edtech – A deeper dive. [Video]. YouTube. https://youtu.be/is60vMnzYrs?si=87NhAU9t8L8isaVC

Le Cunff, A.L., Giampietro, V., & Dommett, E. (2024). Neurodiversity and cognitive load in online learning: A systematic review with narrative synthesis. *Educational Research Review, 43*. https://doi.org/10.1016/j.edurev.2024.100604

López-Meneses, E., López-Catalán, L., Pelícano-Piris, N., & Mellado-Moreno, P. C. (2025). Artificial intelligence in educational data mining and human-in-the-loop machine learning and machine teaching: Analysis of scientific knowledge. *Applied Sciences, 15*(2), 772. https://doi.org/10.3390/app15020772

McDowall, A., & Kiseleva, M. (2024). A rapid review of supports for neurodivergent students in higher education. Implications for research and practice. *Neurodiversity, 2*, 1-16. http://dx.doi.org/10.1177/27546330241291769

Meijs, C., Gijselaers, H. J. M., Xu, K. M., Kirschner, P. A., & De Groot, R. H. M. (2021). The relation between cognitively measured executive functions and reported self-regulated learning strategy use in adult online distance education. *Frontiers in Psychology, 12*. https://doi.org/10.3389/fpsyg.2021.641972

Mishra, S. (2024). Artificial intelligence in neurodiversity: Advancing diagnosis, treatment, and support. *International Journal of Computer Engineering and Technology (IJCET), 15*(4), 330-338. https://doi.org/10.5281/zenodo.13236325

Mollick, E., & Mollick, L. (2023). Assigning AI: Seven approaches for students, with prompts. *arXiv preprint arXiv:2306*.10052. https://arxiv.org/pdf/2306.10052

Mehrfar, A., Zolfaghari, Z., Bordbar, A., & Karimimoghadam, Z. (2024, February). The evolution of e-learning towards the emergence of artificial intelligence (a narrative review). In *2024 11th International and the 17th National Conference on E-Learning and E-Teaching (ICeLeT)* (pp. 1-5). IEEE. https://doi.org/10.1109/ICeLeT62507.2024.10493104

Meylani, R. (2024). A critical glance at adaptive learning systems using artificial intelligence: A systematic review and qualitative synthesis of contemporary research literature. *Batı Anadolu Eğitim Bilimleri Dergisi, 15*(3), 3519–3547. https://doi.org/10.51460/baebd.1525452

Mitre, X., & Zeneli, M. (2024). Using AI to improve accessibility and inclusivity in higher education for students with disabilities. In *2024 21st International Conference on Information Technology Based Higher Education and Training* (pp. 1–8). https://doi.org/10.1109/ITHET61869.2024.10837607

Ng, D. T. K., Tan, C. W., & Leung, J. K. L. (2024). Empowering student self-regulated learning and science education through ChatGPT: A pioneering pilot study. *British Journal of*

Educational Technology, 55(4), 1328–1353. https://doi.org/10.1111/bjet.13454

Oga-Baldwin, W. Q. (2015). Supporting the needs of twenty-first century learners: A self-determination theory perspective. Motivation, leadership and curriculum design: Engaging the net generation and 21st century learners, 25-36. http://ndl.ethernet.edu.et /bitstream/123456789/41596/1/620.Caroline%20Koh.pdf#page=29

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

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., ... & Moher, D. (2021). The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. bmj, 372. http://dx.doi.org/10.1136/bmj.n71

Pagliara, S. M., Bonavolontà, G., Pia, M., Falchi, S., Zurru, A. L., Fenu, G., & Mura, A. (2024). The integration of artificial intelligence in inclusive education: A scoping review. *Information, 15*(12), 774. https://doi.org/10.3390/info15120774

Papalexandratou, P. & Stathopoulou, A. (2024). The use of artificial intelligence in the education of students with learning disabilities. *Global Journal of Engineering and Technology Advances, 21*(3), 033–049. https://doi.org/10.30574/gjeta.2024.21.3.0223

Pierrès, O., Christen, M., Schmitt-Koopmann, F. M., & Darvishy, A. (2024). Could the use of AI in higher education hinder students with disabilities? A scoping review. *IEEE Access*, 12, 27810–27828. https://doi.org/10.1109/ACCESS.2024.3365368

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, 67–73. https://doi.org/10.55549/epess.1381518

Sajja, R., Sermet, Y., Cwiertny, D., & Demir, I. (2023). Integrating AI and learning analytics for data-driven pedagogical decisions and personalized interventions in education. *arXiv*. https://doi.org/10.48550/arXiv.2312.09548

Sangkala, I., & Mardonovna, N. S. (2024). Artificial intelligence as a personalized tutor in language learning: A systematic review. *KLASIKAL: Journal of Education, Language Teaching and Science, 6*(2), 565–576. https://doi.org/10.52208/klasikal.v6i2.1193

Santos, S. M., Da Silva, C. G., De Carvalho, I. E., De Castilho, L. P., Meroto, M. B., Tavares, P. R., Pires, R. D., & Moniz, S. S. (2024). The art of personalization of education: Artificial intelligence on the stages of special education. *Contribuciones a las Ciencias Sociales, 17*(2). https://doi.org/10.55905/revconv.17n.2-008

Siemens, G., Marmolejo-Ramos, F., Gabriel, F., Medeiros, K., Marrone, R., Joksimovic, S., & de Laat, M. (2022). Human and artificial cognition. Computers and Education: Artificial Intelligence, 3, 100107. https://doi.org/10.1016/j.caeai.2022.100107

Southon, C. (2022). The relationship between executive function, neurodevelopmental disorder traits, and academic achievement in university students. *Frontiers in Psychology, 13*. https://doi.org/10.3389/fpsyg.2022.958013

Taylor, C. (2013). Review paper: Cognitive load theory – Sometimes less is more. i-manager's *Journal of School Educational Technologies, 9*(1), 61-68. https://files.eric.ed.gov/fulltext/EJ1098320.pdf

Tenório, K., Santos, J., Accete, V., Remigio, S., Da Silva, A. P., Dermeval, D., Bittencourt, I. I., & Marques, L. B. (2021). On the joint use of artificial intelligence and brain-imaging techniques in technology-enhanced learning environments: A systematic literature review. *Revista Brasileira de Informática Na Educação, 29*, 502–518. https://doi.org/10.5753/rbie.2021.29.0.502

Vera Carrasco, L. M., Aguirre Hojas, R. R., Castro Mera, J. S., Cedeño Salazar, P. A., & Seis Mendoza, L. A. (2024). Implementación de Inteligencia artificial para promover la inclusión de estudiantes con necesidades educativas especiales en la Educación Superior [Implementation of artificial intelligence to promote the inclusion of students with special educational needs in Higher Education]. *LATAM Revista Latinoamericana De Ciencias Sociales Y Humanidades, 5*(5), 881 – 893. https://doi.org/10.56712 /latam.v5i5.2654

Wheeler, D. (2024). Instructional design on neurodiverse learners' cognitive load in online learning environments: A phenomenological study (Publication No. 31335052) [Doctoral dissertation, South College]. ProQuest Dissertations & Theses Global. http://mutex.gmu.edu/login?url= https://www.proquest.com/ dissertations-theses/instructional-design-on-neurodiverse-learners/docview/3074113209/se-2

Xu, Z. (2024). AI in education: Enhancing learning experiences and student outcomes. *Applied and Computational Engineering, 51*(1), 104-111. https://pdfs.semanticscholar.org/d331/7f3a95ba2c4cdb3626d962bde2322483bea3.pdf https://doi.org/10.1155/2022%2F1263555

Yap, J. R., Aruthanan, T., & Chin, M. (2025). Artificial intelligence in dyslexia research and education: A scoping review. *IEEE Access, 13*, 7123–7134. https://doi.org/10.1109 /ACCESS.2025.3526189

Yu, L., Shek, D. T., & Zhu, X. (2018). The influence of personal well-being on learning achievement in university students over time: Mediating or moderating effects of internal and external university engagement. *Frontiers in Psychology, 8*, 2287.

https://doi.org/10.3389/fpsyg.2017.02287

Zhang, N., Leong, W. Y., Zhang, T., & Wei, C. (2024). Artificial intelligence in engineering Education: A review of pedagogical innovations. *INTI Journal, 2024*(46), 1-10. https://doi.org/10.61453/intij.202446

Appendix A

Study Characteristics

This table lists each study along with its research focus.

Table 1: Characteristics of Included Studies

Study	Study Type	Focus Area	Population Studied	Implementation Context
Alotaibi, 2024	Systematic Review	AI and Learning Management System (LMS) Integration	Higher Education students	Higher Education Institutions
Chalkiadakis et al., 2024	Systematic Review	AI and Virtual Reality (VR) in educational inclusion	Students with disabilities	No specific mentions
Ejjami, 2024	Empirical Study – Qualitative, Exploratory Multiple-Case Study	Adaptive Personalization Theory of Learning	Higher Education students	Higher Education Institutions
El Naggar et al., 2024	Empirical Study - Qualitative	AI-mediated discussions for exceptional learners	Exceptional learners	No specific mentions
Faruqui et al., 2024	Empirical – Quantitative	AI-powered adaptive learning	Undergraduate students	Sam Houston State University, Engineering Technology Department
Gupta, 2024	Empirical Study – Mixed Methods	Adaptive Learning Systems	No specific mentions	No specific mentions
Herrería Gallardo et al., 2024	Systematic Review	AI integration in inclusive education strategies	Students in higher education	Higher Education institutions
Hyatt & Owenz, 2024	Empirical Study – Mixed Methods	Universal Design for Learning (UDL) and AI	Graduate student, 30% with learning disabilities	Graduate level courses in Student Affairs
Jiali, 2024	Systematic Review	AI in personalized learning	K-12 and Higher Education students	Schools and Universities
Lopez-Meneses et al., 2025	Systematic Review	AI in educational data mining and machine	No specific mentions	No specific mentions

		learning to improve adaptive and personalized learning		
Meylani 2024,	Systematic Review w/a Qualitative Thematic Synthesis	AI-powered adaptive learning systems	No specific mentions	No specific mentions
Mitre & Zeneli, 2024	Exploratory Literature Review	AI for accessibility and inclusivity	Students with disabilities in higher education	Higher Education Institutions
Pagliara et al., 2024	Scoping Review	AI in inclusive education	Individuals with disabilities	No specific mentions
Papalexandratou & Stathopoulou, 2024	Systematic Review	AI in education for students with learning disabilities	Students with learning disabilities	No specific mentions
Pierrès et al., 2024	Systematic Review	AI use for students with disabilities	Students with disabilities in higher education	Higher Education Institutions
Sangkala & Mardonovna, 2024	Systematic Review	AI as a personalized tutor in learning language	Language learners	No specific mentions
Santos et al., 2024	Literature Review	AI in special education	Students with disabilities and special needs	No specific mentions
Vera Carrasco et al., 2024	Exploratory Literature Review	AI and Learning Management System (LMS) Integration	Higher Education Students	Higher Education Institutions
Yap, 2025	Scoping Review	AI in dyslexia research and education	Individuals with dyslexia	No specific mentions
Zhang et al., 2024	Systematic Review	AI in education for students with learning disabilities	Engineering students	No specific mentions

Appendix B

AI-Enabled Personalization Strategies

This table lists each study and the strategies it presents for AI-enabled personalization.

Table 2: AI-Enabled Personalization Strategies

Study	**Technology Type**	**Personalization Method**	**Learning Context**	**Accessibility Features**
Alotaibi, 2024	AI-powered conversational agents & Adaptive assessments	Personalized learning paths	Higher Education	No specifics mentioned
Chalkiadakis et al., 2024	AI-driven adaptive systems & Virtual Reality (VR)	Dynamically tailoring learning experiences	No specifics mentioned	No specifics mentioned
Ejjami, 2024	AI-powered algorithms	Real-time Adaptive assessments & Cognitive scaffolding	Higher Education	No specifics mentioned
El Naggar et al., 2024	AI-mediated discussions	Personalized and intellectually stimulating experiences	No specifics mentioned	No specifics mentioned
Faruqui et al., 2024	Large Language Models (LLMs) & Retriever-Augmented Generation (RAG)	Real-time & Context-aware adaptive support	Engineering courses	User Interface/ User Experience (UI/UX) design adaptions
Gupta, 2024	AI-powered algorithms	Real-time tailoring of content and assessment	No specifics mentioned	No specifics mentioned
Herrería Gallardo et al., 2024	Intelligent tutoring systems, Virtual assistants, & Predictive analytics tools	Adapting content and teaching methods to individual needs	Higher Education	Voice recognition software, & Automated reading assistants
Hyatt & Owenz, 2024	No specifics mentioned	Multiple options to demonstrate learning	Graduate level courses	Universal Design for Learning (UDL)
Jiali, 2024	Adaptive learning systems & Intelligent Tutoring Systems (ITS)	Tailoring content based on learner understanding and speed	K-12 and Higher Education	Text-to-speech Translation tools

Lopez-Meneses et al., 2025	Educational Data Mining (EDM) & Human-Assisted Machine Learning (HITL-MIL)	Identifying learning patterns and individual needs	No specifics mentioned	No specifics mentioned
Meylani 2024,	Machine Learning algorithms & Natural Language Processing (NLP)	Adapting content, pace, and assessments	No specifics mentioned	No specifics mentioned
Mitre & Zeneli, 2024	Assistive technologies, Adaptive-learning systems, & Generative-AI (Gen-AI) chatbots	Creating personalized learning paths	Higher Education	No specifics mentioned
Pagliara et al., 2024	Text-to-speech, Speech-to-text, & Computer-to-vision	Adaptive learning platforms	No specifics mentioned	Assistive systems
Papalexandratou & Stathopoulou, 2024	No specifics mentioned	No specifics mentioned	No specifics mentioned	No specifics mentioned
Pierrès et al., 2024	No specifics mentioned	No specifics mentioned	Higher Education	No specifics mentioned
Sangkala & Mardonovna, 2024	AI-powered tools, Natural Language Processing (NLP), & Chatbot tutors	Tailoring content based on learner data	No specifics mentioned	No specifics mentioned
Santos et al., 2024	Adaptive learning systems & Advanced screen readers	Adapting content based on individual needs and progress	No specifics mentioned	Image recognition software
Vera Carrasco et al., 2024	Advanced screen readers & Voice recognition systems	Adapting resources and environments to individual needs	Higher Education	Voice commands Detailed descriptions
Yap, 2025	No specifics mentioned	No specifics mentioned	No specifics mentioned	No specifics mentioned
Zhang et al., 2024	Intellegent tutoring systems & Adaptive learning platforms	Personalized curriculum design	No specifics mentioned	No specifics mentioned

Appendix C

Educational Outcomes and Effectiveness

This table presents the interventions, the resulting outcomes, and the success factors and limitations mentioned in the study.

Table 3: Educational Outcomes and Effectiveness

Study	Intervention Type	Measured Outcomes	Success Factors	Limitations
Alotaibi, 2024	AI-Learning Management System (LMS) integration	Enhanced educational quality & Improved performance	Personalized learning paths	Data privacy concerns
Chalkiadakis et al., 2024	AI and Virtual Reality (VR) in educational inclusion	Tailored learning experiences	Immersive, multi-sensory environments	Implementation challenges
Ejjami, 2024	Adaptive Personalization Theory	Improved learning outcomes & Increased motivation	Real-time adaption & Cognitive scaffolding	No specifics mentioned
El Naggar et al., 2024	AI-mediated discussions	Enhanced engagement & Tailored Instruction	Personalized experiences	Confirmation bias & Information overload
Faruqui et al., 2024	AI-powered adaptive learning	Expected improvements in knowledge gains & satisfaction	Real-time, context-aware support	Study in process so the results are not currently available
Herrería Gallardo et al., 2024	AI-powered personalized learning	Improved engagement & Personalized support	Tailored content & Early interventions	No specifics mentioned
Gupta, 2024	Adaptive Learning Systems	Personalized educational outcomes	Real-time feedback & Adaptive content	No specifics mentioned
Hyatt & Owenz, 2024	AI-based assignment with Universal Design for Learning (UDL)	Student satisfaction & Engagement	Multiple assessment options	Small sample size
Jiali, 2024	AI-powered adaptive learning	25% increase in test scores & Enhanced engagement	Personalized feedback & Early interventions	Potential algorithmic bias

Lopez-Meneses et al., 2025	AI in educational data mining	Improved personalized learning & Enhanced student tracking	Identification of learning patterns	No specifics mentioned
Meylani, 2024	AI-powered adaptive learning	Improved learning outcomes & Enhanced engagement	Personalization & Gamification	No specifics mentioned
Mitre & Zeneli, 2024	AI for accessibility and inclusivity	Increased access to resources & Personalized learning	Personalized learning paths	No specifics mentioned
Pagliara et al., 2024	AI in inclusive education	Enhanced learning effectiveness & Improved engagement	Tailored learning supports	No specifics mentioned
Papalexandratou & Stathopoulou, 2024	AI for learning disabilities	Improved academic performance & Reduced inequalities	No specifics mentioned	No specifics mentioned
Pierrès et al., 2024	AI for students with disabilities	Potential for personalization and timely feedback	No specifics mentioned	Lack of inclusion in research
Sangkala & Mardonovna, 2024	AI in language learning	Improved education outcomes & Enhanced motivation	Tailored instruction & 24/7 access	Data privacy concerns
Santos et al., 2024	AI in special education	Improved engagement & Better content understanding	Personalized teaching & Adaptive content	Ethical concerns
Vera Carrasco et al., 2024	AI for special education needs	Improved learning effectiveness & Enhanced autonomy	Personalized content & Accessibility tools	No specifics mentioned
Yap, 2025	AI in dyslexia	Improved early detection & Personalized interventions	Culturally relevant tools	Limited empirical evidence
Zhang et al., 2024	AI in engineering education	No specifics mentioned	No specifics mentioned	No specifics mentioned