AI- POWERED ADAPTIVE LEARNING PLATFORM

B.Sandhya[1], Garapati Sai Harshitha Devi[2], Cheripelli Pooja[3], Chennoju Srinath[4], Beesam Navya Reddy[5]

[1] Associate Professor, Dept. of AI-ML, Sri Indu College of Engineering and Technology, Hyderabad,
[2 3 4] Research Student, Dept. of AI-ML, Sri Indu College of Engineering and Technology, Hyderabad

[1]Department Agricultural and Resource Economics, University of California, Berkeley, California, USA

[2]Department of Trade and Finance, Faculty of Economics and Management, Czech University of Life Sciences Prague, Prague, Czech Republic

[3]Department of Pedagogy and Psychology, Kuban State University, Krasnodar, Russia

[4]Department of Strategic and Innovative Development, Faculty 'Higher School of Management', Financial University under the Government of the Russian Federation, Moscow, Russia

[5]Joint-Stock Company "RPC "Krypten", Moscow, Russia

[6]Department of Accounting and Auditing, National Research University "Tashkent Institute of Irrigation and Agricultural Mechanization Engineers" (TIIAME National Research University), Tashkent, Uzbekistan

[7]Department of Science and Rating, Diplomat University, Tashkent, Uzbekistan

[8]University Department of Educational Psychology, Moscow City Pedagogical University, Moscow, Russia

Correspondence
Wadim Strielkowski, Department Agricultural and Resource Economics, University of California, Berkeley, 303 Giannini Hall, California 94720, USA.
Email: strielkowski@berkeley.edu; strielkowski@pef.czu.cz

Funding information
Kuban Science Foundation, Grant/Award Number: MFI-20.1/80

Abstract

This paper scrutinizes how adaptive learning technologies and artificial intelligence (AI) are transforming today's education by making it personalized, accessible, and efficient as well as leading people to accepting, addressing, and mitigating sustainable development. Recently, education witnessed a remarkable technological surge driven by various advances in technology, which can be demonstrated by the increase of the number of scientific publications on this topic from just 1 in 1990 to 636 in 2023. Ongoing digitalization and technological revolution in education together with the novel approach to respect each student's unique learning style and abilities paved the way for adaptive learning technologies represented by the innovative tools that personalize educational experiences to cater to individual learners. All of that contributes to preparing more educated and informed citizens, drives innovation, and supports economic growth necessary for achieving a sustainable future. Our bibliographic study employs VOSviewer to conduct a bibliometric analysis of a total number of 3518 selected publications using the keywords "adaptive learning" and "AI" (represented by articles, proceeding papers, and book chapters) indexed in the Web of Science (WoS) database from 1990 to 2024. Our results demonstrate that recent technological changes played a key role in transforming adaptive learning, which was rather reinforced by the "digital surge" in education brought about by the COVID-19 pandemic. Our findings can be useful for further development in the field of adaptive education where they can be employed by the relevant stakeholders and policymakers as well as by the scholars and researchers.

KE YWOR DS
adaptive learning, artificial intelligence, bibliographic analysis, sustainable development

1 | INTRODUCTION

Education has always been an important aspect of the development of any society. It has also undergone numerous profound changes over time needed to reflect most recent challenges such as technolog- ical progress or global warming and climate change. (Akour & Alenezi, 2022; Alenezi, 2023). Nowadays, as we are entering the new post-COVID era that mark the transformation of the coronavirus pan- demic (2020–2023) into the endemic, adaptive learning technologies, and artificial intelligence (AI) are revolutionizing education and it role in education for sustainability (EfS) like never before (Adiguzel et al., 2023; de Vries, 2022; Jing et al., 2023).

Adaptive learning technologies refer to educational systems that leverage data analytics and AI to personalize the learning experience. These technologies dynamically adjust the presentation of educational content based on an individual student's performance, learning pace, and preferences (Gligorea et al., 2023; Khan et al., 2022). By continu- ously analyzing data on student interactions, adaptive learning tech- nologies provide customized support, targeted feedback, and optimized learning pathways to enhance student engagement and outcomes.

The arrival of AI in education marks a revolutionary shift, starting an era where personalized, adaptive learning becomes a reality. This transformative impact of AI paves the way for innovative approaches in sustainable education, reshaping traditional teaching methods into dynamic, learner-centered experiences. In the short run, the advent of AI might not change the education, but in the long run it would change it fundamentally.

Adaptive learning technologies and AI contribute to achieving sustainable future and it is quite straightforward to show how they do that: they help to tailor and provide education for all fostering a more education population capable of tackling complex global challenges, including sustainability. Better educated individuals make informed decisions about their daily lives and living environments, which in turn leads to more sustainable practices and policies. In addition, they pro- mote innovation and solving most pressing global issues such as sus- tainability, climate change, and resource management. Finally, they help to shape up education that drives economic growth, which is cru- cial for funding and implementing sustainable initiatives.

The emergence of adaptive learning constitutes an evolutionary process that stems from centuries-long efforts to improve education. In ancient times, education was primarily limited to privileged elites who had access to personal tutors or attended prestigious institutions (Worth et al., 2023). Medieval universities used to be the places where the offspring of the elites would meet to study, mingle, make friends, and later in their lives strike powerful alliances for their fur- ther endeavors (Nureev et al., 2020). However, with time came advancements such as the printing press in the 15th century, which democratized knowledge dissemination through books and opened it to the wider masses (Zarifian et al., 2022). Then the Industrial Revolu- tion in the 18th century brought about further changes in education as the need for basic literacy and numeracy skills became indispens- able for an increasingly industrialized world (Purwanto et al., 2023). In the 18th century, it was mass public schooling systems that opened education to the masses and introduced a major breakthrough. Most recently, the next breakthrough was driven by technology that once again helped to transform education. The advent of personal com- puters introduced interactive multimedia resources into classrooms while distance learning programs enabled students to access educa- tional content remotely (Ferri et al., 2020). Finally, the spread of the Internet, first in the form of personal computing and then through mobile computing (i.e. using ubiqutious smartphones), made informa- tion and knowledge available for anyone virtually everywhere (with spatial computing being the next awaited breakthrough in education). Today, the main issue is not how to find some specific information but where to look for it and how to filter it and interpret the obtained data (Alashhab et al., 2021).

These developments laid the groundwork for adaptive learning technologies by demonstrating how technology could enhance educa- tional experiences beyond traditional teaching methods. With it, AI and data-driven tools are applied to personalize and enhance (Lameras & Arnab, 2021; Tapalova & Zhiyenbayeva, 2022).

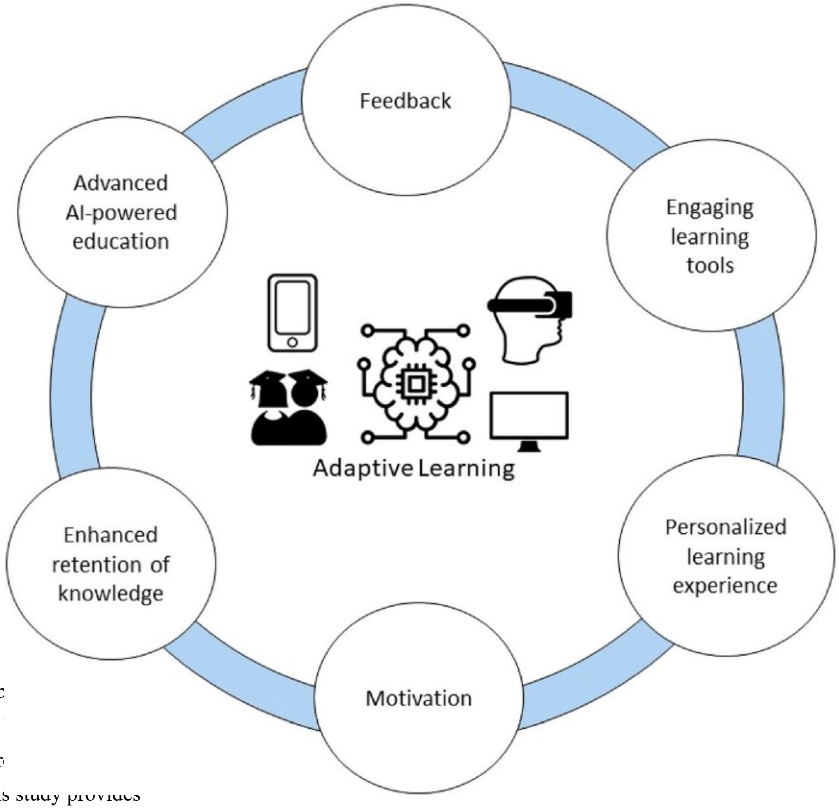
Figure 1 that follows offers a detailed visualization of the contem- porary adaptive learning framework. This framework is supported by several technological pillars: personal computing, mobile computing, and spatial computing. It integrates advanced AI and augmented real- ity (AR) within educational approaches. Additionally, the figure illus- trates engaging learning tools that are part of this framework. It also highlights personalized learning experiences designed for individual learners. Digitalized feedback mechanisms, aimed at enhancing the learning experience, are another key component depicted in the fig- ure. Finally, the framework includes strategies for improved knowl- edge retention, which serve to increase learner motivation (see Figure 1).

Nevertheless, while adaptive learning technologies hold immense promise for revolutionizing education, many serious challenges remain. For instance, there are privacy concerns surrounding student data and the ethical implications of relying heavily on AI algorithms are areas that need careful consideration (Nguyen et al., 2023).

Our study aims at exploring the development of sustainable edu- cation with regard to the technological advancements and societal changes. In particular, it focuses on the impact of novel adaptive learning technologies and AI on education, especially with regard to the post-COVID sustainable education of the 21st century. Further- more, the paper works towards critically analyzing the challenges and opportunities associated with adaptive learning technologies, concen- trating on the ethical implications and privacy concerns related to use of AI algorithms. The ultimate goal is to provide a comprehensive understanding of the potential of adaptive learning in revolutionizing education while addressing the complexities and limitations associ- ated with its implementation.

The novelty of this paper lies in its comprehensive analysis of the intersection between AI-driven adaptive learning technologies and sustainable education. While previous studies have explored adaptive learning and AI separately, this manuscript offers a unique perspective by examining how these technologies can be leveraged to not only

FIGURE 1 The framework for modern adaptive learning using personal computing, mobile computing, as well as spatial computing. *Source*: Own development.



enhance educational outcomes but also contribute to the b sustainability. By aligning educational practices with the Sustainable Development Goals (SDGs), particularly in pr education (SDG 4) and reducing inequalities (SDG 10), this study provides a fresh approach to understanding the role of technology in education.

The research topic tackled in this paper is important and timely due to its alignment with societal needs for sustainable education, its focus on cutting-edge technological advancements, its emphasis on individualized learning, and its scholarly rigor demonstrated through advanced analytical methods. The research addresses pressing educa- tional challenges amplified by the digital surge accelerated by the COVID-19 pandemic, making it a crucial and timely contribution to the field of education. The paper is centered on the following three research questions (RQs):

1. RQ1. How have adaptive learning technologies and AI transformed contemporary education and contributed to the vision of sustainable educa- tion in the post-COVID era?
2. RQ2. What are the main challenges associated with implementing adaptive learning technologies?
3. RQ3. What key trends and patterns can be iden- tified in the bibliometric analysis of the relevant publications on adaptive learning and AI, and

Through a bibliometric analysis and case studies, this paper iden- tifies key trends, challenges, and opportunities in the implementation of adaptive learning technologies. It also offers practical insights into how these technologies can be effectively integrated into educational systems to foster sustainable development. What sets this study apart is its focus on the dual impact of AI-driven adaptive learning: improv- ing personalized learning experiences while simultaneously advancing sustainability initiatives. This dual focus is particularly relevant in the current global context, where there is a growing recognition of the need for educational practices that are both effective and aligned with long-term sustainability goals.

The paper is structured in the following manner: Section 2 pre- sents the structured literature review on adaptive learning and AI in enhancing and revolutionizing education. Section 3 explains the role of the adaptive learning in sustainable education of the 21st century. Section 4 contemplates over the challenges in implementing adaptive learning technologies using some examples and case studies. Section 5 features materials and methods describing the bibliometric analysis conducted and reported in this paper. Section 6 presents the results of the bibliometric analysis. Finally, the conclusions and implications section summarizes the results of this study, discusses its limitations, and offers the pathways for further research in this area.

2 | LITERATURE REVIEW

2.1 | Adaptive learning as a breakthrough in personalized education

Adaptive learning technologies and AI made a breakthrough in con- temporary personalized education and contributed to the vision of sustainable education in the post-COVID era. In general terms, adap- tive learning can be best understood as an intelligent system that leverages data analytics and machine learning algorithms to provide personalized instruction (Koutsantonis et al., 2022). Unlike traditional one-size-fits-all teaching methods, adaptive learning adapts the con- tent, pace, and delivery of instruction based on an individual student's strengths, weaknesses, and learning preferences (Smyrnova-Trybulska et al., 2022).

Empirical evidence supports the claim that adaptive learning tech- nologies significantly improve educational efficiency. Thence, the implementation of adaptive learning platforms might lead to higher pass rates and improved student retention compared to traditional teaching methods (Contrino et al., 2024; Demartini et al., 2024). For instance, one meta-analysis paper (García-Martínez et al., 2023) reviewed 25 studies on adaptive learning technologies and concluded that these technologies consistently enhance student engagement and performance across various educational contexts. All of this illus- trates the substantial impact of adaptive learning technologies on edu- cational efficiency, providing concrete evidence to support this claim.

In recent years, adaptive learning and personalized education encountered the growing interest of the general public and expert alike. Figure 2 below shows the dynamics of the frequency of search requests (Interest over Time—search interest relative to the highest point on the chart for the given region and time and ranging from 0 (zero popularity on no data) to 100 (peak popularity)) of the search terms “personalized education” and “adaptive learning” for the last 20 years from 2004 until 2024.

Figure 2 was generated through an analysis of data retrieved from the Google Trends toolkit, a tool made available by the Google search engine. The toolkit identifies the changes in search queries of the main relevant concepts helping the researchers to assess the peak periods with the periods of the most significant changes in the searches on the Internet (Google Trends, 2023).

The customization used in adaptive learning ensures that learners receive targeted support and engage with materials at their optimal level of challenge. At the core of adaptive learning is its data-driven nature. Learning platforms equipped with adaptive technologies col- lect vast amounts of data about students' performance, interactions, and progress throughout their educational journey (Kamalov et al., 2023). These platforms use this data to create detailed learner profiles that capture each student's knowledge gaps, misconceptions, preferred learning styles, and areas of proficiency. With these learner profiles in hand, adaptive systems employ sophisticated algorithms to analyze the data and make informed decisions about what content a student should learn next or how it should be delivered (Wolff et al., 2023). For instance, if a student struggles with fractions but excels at geometry concepts, the system will identify this discrepancy through data analysis and adjust the instructional materials accord- ingly by providing additional practice or alternative explanations

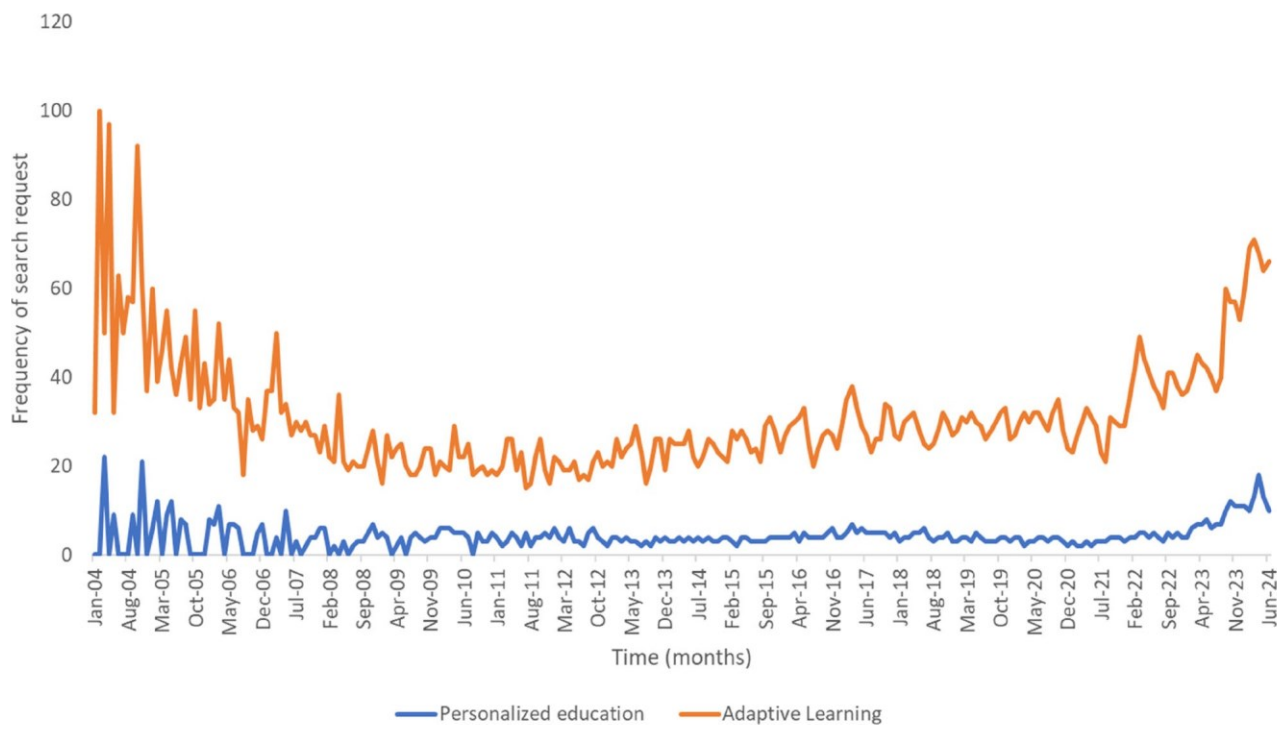


FIGURE 2 Dynamics of frequency of search of the terms of “personalized education” and “adaptive learning” (2004–2024). *Source*: Own results based on Google Trends.

specifically targeting fractions. Moreover, adaptive learning does not limit itself to adjusting content but also considers other crucial factors such as pacing and feedback provision. The system monitors students' progress in real-time and adapts to the pace at which new material is introduced based on their demonstrated mastery level. This ensures that learners are neither overwhelmed nor bored by content that is too easy or too challenging for them (Avram & Pop, 2023; Wolff et al., 2023). Additionally, adaptive systems provide immediate feed- back throughout the learning process. This timely feedback not only enhances students' understanding but also promotes metacognition and self-regulation skills as they actively reflect on their progress (Garrison, 2022).

Thence, the benefits of adaptive learning extend beyond individ- ual learners to educators as well. Adaptive systems use machine learn- ing to assess the learning patterns and study progress of the students in real time and to report them to tutors who can, in turn, quickly adapt their teaching strategies, intervene when needed or adjust their lectures according to the students' progress and understanding of the material.

2.2 | AI in revolutionizing education: The power of machine learning

One significant advantage AI brings to education is its ability to ana- lyze large amounts of data quickly. By collecting vast quantities of stu- dent information, such as performance data, preferences, and learning patterns, AI algorithms can create individualized learning paths for each student (Shemshack et al., 2021). Adaptive learning platforms leverage this capability by continuously monitoring students' progress and adapting instructional content accordingly. This personalized approach ensures that students receive targeted support where they need it most (Muñoz et al., 2022).

It is important to differentiate between various types of adaptive learning technologies, as they offer different functionalities and cater to diverse educational needs. Content-based adaptive systems are designed to personalize the instructional content delivered to stu- dents, adjusting based on their progress and learning preferences. These systems are particularly effective in subjects where the learning material is cumulative, such as mathematics or language learning. Assessment-based adaptive systems, on the other hand, focus on tai- loring assessments and providing personalized feedback, dynamically adjusting the difficulty level of tasks to match the student's perfor- mance. Finally, integrated adaptive systems combine both content delivery and assessment features, offering a comprehensive solution that supports students through personalized learning paths, continu- ous assessment, and targeted interventions. Understanding these dis- tinctions is essential for educators and institutions when selecting the most suitable adaptive learning technologies for their specific contexts.

Several case studies or examples can be mentioned here to dem- onstrate the successful application of AI in adaptive learning environ- ments: In the United States, Arizona State University (ASU) partnered with Knewton to implement an adaptive learning platform in college- level math courses. The AI-driven platform analyzed individual student data to identify areas of struggle and provided personalized recom- mendations. As a result, students who used the platform achieved higher pass rates compared to those who did not, illustrating the effectiveness of AI in enhancing academic performance (Maxfielf, 2023).

Another example is DreamBox Learning, an adaptive math pro- gram used in elementary schools, leverages AI to track students' progress in real-time. By identifying knowledge gaps and adjusting les- sons accordingly, the program has significantly improved math profi- ciency among its users (Foster, 2023). A study conducted by Harvard University found that students who used DreamBox regularly demon- strated substantial gains in math skills compared to their peers using traditional methods (Barbieri et al., 2020).

Yet another real-world example is Carnegie Learning platform that utilized AI-powered adaptive technology to enhance its middle school math curriculum. The platform collected data on student per- formance and generated personalized assignments tailored to each student's strengths and weaknesses. Schools implementing Carnegie Learning's program reported improved test scores and greater student engagement (Wested., 2017). In addition to these examples, many universities have embraced adaptive learning platforms like Smart Sparrow and CogBooks to enhance teaching effectiveness across diverse subjects such as science, engineering, and humanities (Li et al., 2021; Putra et al., 2022). All of these case studies discussed above clearly demonstrate the transformative impact of adaptive learning on education.

Machine learning algorithms also facilitate real-time feedback for students. Traditional assessment methods often provide feedback after completion or during specific intervals, limiting immediate cor- rections or improvements (Sharma et al., 2020). However, with AI- driven systems, learners receive instant feedback on their work through automated grading systems or virtual tutors capable of guid- ing at any time. This immediate response helps students identify their mistakes promptly and make necessary adjustments while still engag- ing with the topic at hand (Celik et al., 2022).

With regard to the above, the relationship between adaptive learning technologies and traditional assessment methods appears to be a critical area of consideration in education as well in the public sector (Marjerison & Gatto, 2024). While traditional assessments, such as standardized tests and exams, provide summative evaluations at specific points in time, adaptive learning technologies offer continu- ous, formative assessments that adjust to the learner's needs in real time. This ongoing evaluation process allows for more personalized feedback and supports the individual learning journey. However, inte- grating these adaptive approaches with traditional assessment methods poses challenges, such as aligning real-time feedback with standardized criteria and ensuring consistency in measuring student progress (Mirata et al., 2020). A balanced approach that combines the strengths of both traditional and adaptive assessments can enhance the overall evaluation process, providing educators with a more com- prehensive understanding of student learning outcomes which is especially relevant in the era of upcoming Industry 5.0 that offers innovative new prospects leading to the production of more environ- mentally friendly projects, services, and products (Baig & Yadegaridehkordi, 2024).

Moreover, machine learning algorithms in education revolution- ized the way feedback is delivered, enabling students to receive real- time responses to their work. This immediacy in feedback not only assists learners in promptly identifying and correcting their mistakes but also ensures continuous engagement and adjustment within the learning process, thereby significantly enhancing learning outcomes.

Another aspect where machine learning enhances education is in creating immersive and interactive experiences for learners. Virtual reality (VR) and AR technologies powered by AI enable students to explore subjects like history or science through simulated environ- ments that would otherwise be inaccessible or dangerous in real life (Scavarelli et al., 2021). For instance, VR can transport history, stu- dents, to ancient civilizations or allow biology classes to dissect virtual organisms without any ethical concerns. Moreover, leveraging the power of machine learning enables educators to predict future stu- dent performance accurately. By analyzing patterns from past data combined with contextual factors like attendance records or engage- ment levels, algorithms can forecast potential challenges a student might face in their academic journey. With this information, teachers can intervene early, providing timely support, and guidance to help struggling students before they fall behind (Atalla et al., 2023; Cheng et al., 2023).

In addition, the role of AI in revolutionizing education also extends beyond the classroom. It can be used for routine administra- tive tasks such as preparing study schedules and plans, progress moni- toring, or grading, and marking. However, it cannot completely replace humans in any of those processes. The human touch remains vital for fostering creativity, critical thinking skills, and social– emotional development—areas where machines currently lack profi- ciency (Heim et al., 2023).

2.3 | Intelligent tutoring systems: Enhancing student engagement and performance

With the rapid rise of adaptive learning and AI, education has wit- nessed a significant transformation. Intelligent tutoring systems (ITS) have emerged as powerful tools that not only enhance student engagement but also improve academic performance (Guo et al., 2021). ITS addresses this issue by offering individualized instruction that aligns with students' knowledge gaps, learning styles, and pace. By employing advanced machine learning techniques, intelli- gent tutoring systems analyze student data in real time. They monitor their progress, identify areas of weakness, and provide targeted feed- back for improvement (Li & Xia, 2020; Mahmood et al., 2022).

This personalized approach ensures that students receive tailored support precisely where they need it most. As a result, learners feel more motivated and engaged in their studies as they witness tan- gible progress. Furthermore, intelligent tutoring systems foster independent learning by encouraging students to take ownership of their educational journey. Through adaptive algorithms, ITS guides learners through challenging concepts at an appropriate level of diffi- culty while gradually building their skills (Benvenuti et al., 2023). This approach promotes self-directed learning habits that are crucial for lifelong success. Beyond enhancing engagement levels, intelligent tutoring systems have also demonstrated significant improvements in academic performance across various subjects (Chen et al., 2020). Many studies demonstrated that students using ITS outperform those relying solely on traditional teaching methods or even computer- based instruction without adaptability (Muca, Cavallini, et al., 2023; Rejmi & Rasli, 2022). Thence, intelligent tutoring systems are revolu- tionizing education by providing personalized instruction tailored to individual student needs. By leveraging AI algorithms and real-time data analysis, these systems not only enhance engagement levels but also boost academic performance across a wide range of subjects.

2.4 | Novel educational solutions: Transforming traditional teaching methods

In the past few decades, AI and adaptive learning took education by surprise helping to reinvent the traditional methods of teaching for both lecturers and students and providing personalized educational experiences in real time. Traditional teaching methods that used to rely on a one-size-fits-all approach, where educators deliver content at a fixed pace without considering variations in student abilities or interests, suddenly became obsolete (Alamri et al., 2021).

However, with AI-powered platforms, students can receive tai- lored instruction that caters to their unique strengths and weak- nesses. By analyzing vast amounts of data, such systems can identify individual learning patterns and adjust their curriculum accordingly (Tapalova & Zhiyenbayeva, 2022). This personalized approach not only enhances student engagement but also improves overall learning outcomes. Moreover, AI-driven educational solutions offer real-time feedback and assessment capabilities that go beyond what traditional teaching methods can provide (Wongvorachan et al., 2022).

Through continuous monitoring of students' progress, these plat- forms can identify areas where additional support is needed and offer targeted interventions to address those gaps. This instant feedback loop empowers students to take ownership of their learning journey by enabling them to track their progress and make informed decisions about areas requiring further attention (Meng, 2023). Additionally, AI- powered platforms facilitate collaborative learning experiences by connecting students with peers who share similar interests or aca- demic goals. By creating virtual communities, these solutions foster a sense of belonging and encourage knowledge sharing among learners from diverse backgrounds (He et al., 2023). This collaborative environ- ment promotes critical thinking skills, problem-solving abilities, and communication proficiency—essential competencies for success in the digital age (Minyar-Beloroucheva & Sergienko, 2022). With all that, AI-driven educational solutions are transforming traditional teaching methods by providing personalized instruction tailored to individual student needs. With adaptive learning algorithms that analyze vast amounts of data in real time, these platforms offer customized curric- ula while facilitating collaborative experiences among learners.

2.5 | Adaptive assessment systems: Redefining testing and evaluation

The integration of adaptive assessment systems in education has rev- olutionized the field of testing and evaluation. These innovative sys- tems utilize AI algorithms to dynamically adjust the difficulty level and content of assessments based on a student's performance. This per- sonalized approach to testing offers numerous benefits that tradi- tional standardized tests simply cannot match (Maghsudi et al., 2021).

Unlike traditional exams, where students have to wait for days or even weeks for their results, adaptive assessments generate instant feedback. This real-time evaluation allows students to identify their strengths and weaknesses promptly, enabling them to focus on areas that require improvement and reinforcing their learning experience (Chen, 2022). Moreover, adaptive assessment systems offer a more accurate representation of a student's knowledge and skills compared to traditional tests. These systems adapt the difficulty level of ques- tions based on the student's responses, ensuring that each question is appropriately challenging. By tailoring the assessment to an individ- ual's abilities, these systems eliminate the potential biases associated with one-size-fits-all exams and provide a more accurate measure of a student's true capabilities (Owan et al., 2023). Additionally, adaptive assessments encourage active engagement and motivation among students.

As each question is tailored to their specific abilities, students feel challenged but not overwhelmed, fostering a sense of achievement and motivation. Furthermore, adaptive assessment systems enable educators to gather valuable data about individual student perfor- mance as well as overall class progress (Zainuddin et al., 2020). The AI algorithms collect comprehensive data on each student's strengths, weaknesses, learning patterns, and progress over time. This data- driven approach allows teachers to gain insight into individual needs and make informed decisions regarding instructional strategies or interventions tailored specifically for each student (Glover et al., 2023).

2.6 | Adaptive curriculum design: Tailoring education to individual needs

Adaptive learning and AI offer immense potentials in adjusting educa- tion to individual needs. The one-fits-all approach gives way to the AI- powered curriculum design tailored to each student in accordance with her or his abilities and interests. (Jaiswal & Arun, 2021). AI allows to monitor student's learning pace in real time while identifying her or his strengths and weaknesses which generates useful feedback for the teachers and instructors who can adjust their methods and approaches.

With AI-powered curriculum design, personalized learning becomes a reality. Adaptive learning algorithms can customize educa- tional content based on an individual student's proficiency level and learning style (Kabudi et al., 2021; Martin et al., 2020).

In addition, the system can help the student to grasp the new ideas and concepts by offering alternative explanations. Conversely, if a student demonstrates advanced understanding in certain areas, the system can offer more challenging material or opportunities for fur- ther exploration (Kasneci et al., 2023). Furthermore, AI-powered sys- tems facilitate continuous assessment throughout the learning process. Instead of relying solely on standardized tests at predeter- mined intervals, these systems continuously evaluate students' knowl- edge and skills through interactive exercises and quizzes (Vesin et al., 2022).

By providing immediate feedback and adapting the difficulty level based on performance, AI-powered curriculum design fosters an environment where mistakes are seen as opportunities for growth rather than failures. Such curriculum design represents a significant step towards tailoring education to individual needs (Wiggins et al., 2020).

Table 1 that follows summarizes the main provisions and discus- sions stemming from the literature review presented in this section.

2.7 | Limitations of AI in education

Nevertheless, it has to be remembered that while AI has the potential to revolutionize education by providing personalized learning experi- ences and improving efficiency, it is also important to recognize the limitations of this technology as highlighted in the existing literature (Akgun & Greenhow, 2022; Zhai et al., 2021).

One of the significant concerns with AI in education is the poten- tial for algorithmic bias. AI systems that are trained on biased datasets can inadvertently perpetuate or even exacerbate inequalities. For instance, some studies demonstrated that AI algorithms may disad- vantage students from underrepresented groups by providing less accurate or biased feedback, thus impacting their learning outcomes (Baker & Hawn, 2022; Von Winckelmann, 2023).

In addition, the extensive data collection required for AI-driven educational tools raises serious privacy concerns. There is a risk of data breaches, unauthorized access, and misuse of sensitive student information. The literature emphasizes the need for robust data pro- tection measures and clear policies to ensure that student privacy is safeguarded (Berendt et al., 2020).

Furthermore, there is also the risk of over-reliance on AI technol- ogies, where educators and students may depend too heavily on auto- mated systems (Zhai et al., 2024). This reliance can lead to a diminished role for critical thinking and human judgment, as well as a potential decrease in the development of problem-solving skills that are fostered through traditional educational practices.

Another limitation noted in the literature is the potential reduc- tion in meaningful human interactions between teachers and students (Markauskaite et al., 2022). AI systems, while efficient, cannot

TABLE 1 Key elements of AI, novel technologies, and approaches in adaptive learning.

Key elements	Characteristics and main provisions
Adaptive learning	- Uses data analytics and AI to offer personalized instruction - Content, pace, and delivery adapt based on students' strengths, weaknesses, and preferences. - Data-driven nature collects student performance data. - Creates learner profiles for customized learning paths. - Algorithms analyze data for content and delivery decisions. - Adjusts pacing and feedback provision. - Enhances metacognition and self-regulation skills
AI in education	- Analyzes large student data for individualized learning paths. - Offers continuous progress monitoring and content adaptation. - Real-time feedback through automated grading and virtual tutors. - Immersive experiences using VR and AR. - Predicts future student performance for early interventions. - AI assists in administrative tasks, complementing the human touch.
Intelligent tutoring systems	- Offer individualized instruction. - Real-time data analysis for progress monitoring. - Targeted feedback to address weaknesses. - Promote engagement and self-directed learning. - Improve academic performance.
AI-driven novel educational solutions	- Transforms traditional teaching with personalized experiences. - Tailored instruction based on student strengths and weaknesses. - Real-time feedback and assessment. - Continuous monitoring for support and interventions. - Facilitates collaborative learning. - Enhances critical thinking and problem-solving.
Adaptive assessment systems	- Adjust difficulty based on student performance. - Real-time feedback for instant improvement. - Accurate representation of knowledge and skills. - Encourage active engagement and motivation. - Provide valuable data for educators.
Adaptive curriculum design	- Tailors curriculum to individual student needs. - Monitors progress for insights into strengths and weaknesses. - Personalized content based on proficiency and learning style. - Continuous assessment and immediate feedback. - Fosters growth mindset.

Abbreviation: AI, artificial intelligence.
Source: Own results.

replicate the social and emotional learning that occurs through human connections, which are vital for a well-rounded education.

Finally, it is apparent that implementing AI in diverse educational settings presents significant challenges. In resource-constrained envi- ronments, the lack of infrastructure, training, and ongoing support can significantly limit the effective use of AI. Additionally, the high costs associated with acquiring and maintaining AI technologies can be pro- hibitive for many educational institutions.

By acknowledging all these limitations, one can adopt a more cau- tious and balanced approach to integrating AI into education, ensuring that its deployment is done in a way that maximizes benefits while mitigating potential downsides.

3 | ADAPTIVE LEARNING IN SUSTAINABLE EDUCATION

Nowadays, the sustainable future represents one of the main priori- ties for our society and the sustainable education is becoming an important tool how to prepare the next generations to come for face complex environmental and social challenges. Adaptive learning, a dynamic approach that tailors educational experiences to individual needs, holds immense potential in achieving this goal (Gorina et al., 2023; Kadaruddin, 2023).

In particular, adaptive learning technologies can be tailored to address specific learning disabilities or special educational needs, mak- ing education more inclusive. These technologies can be customized to offer personalized learning experiences for students with disabil- ities such as dyslexia, ADHD, autism spectrum disorders, and sensory impairments (Barua et al., 2022; Kem, 2022). For example, adaptive platforms can adjust the difficulty level, provide alternative explana- tions, or present information in various formats (visual, auditory, tac- tile) to suit the learning preferences and challenges of individual students. Additionally, these technologies can offer immediate feed- back and reinforcement, which is particularly beneficial for students who require more frequent support. By incorporating features that specifically cater to the needs of students with learning disabilities, adaptive learning technologies contribute to creating inclusive educational environments where all students have the opportunity to succeed.

Furthermore, adaptive learning can adapt content and delivery methods based on learner progress and preferences. It appears that adaptive learning technologies and AI can significantly contribute to the vision of sustainable education in our post-COVID era with bene- fits in fostering student engagement, enhancing educational out- comes, and promoting lifelong learning for a more sustainable future (Yuan et al., 2021).

To better understand the impact of our study on the SDGs, it needs to be explored how adaptive learning technologies and AI con- tribute to specific SDGs in various contexts (Makurumidze et al., 2024). Primarily, SDG 4 (Quality Education) is directly influenced by adaptive learning technologies that ensure inclusive and equitable quality education by providing personalized learning experiences (Zhukova et al., 2022). These technologies address diverse learning needs and styles, reduce dropout rates, and improve learning out- comes, ensuring that all students, regardless of their background or abilities, have access to high-quality education. The example of Ari- zona State University's implementation of Knewton's adaptive learn- ing platform described above demonstrated the potential of these technologies to enhance educational quality.

Furthermore, adaptive learning technologies support SDG 8 (Decent Work and Economic Growth) by enhancing skill develop- ment and aligning educational content with the demands of the mod- ern workforce. By equipping students with relevant skills and knowledge, these technologies improve employability and productiv- ity, thus contributing to economic growth. DreamBox Learning, an adaptive math program also described above, has been shown to sig- nificantly improve math proficiency among elementary students, lay- ing a strong foundation for their future success in the workforce.

Additionally, adaptive learning technologies contribute to SDG 10 (Reduced Inequalities) by bridging educational gaps between dif- ferent socio-economic groups. Personalized learning experiences ensure that all students, including those from marginalized communi- ties, receive the necessary support to succeed academically (Opesemowo & Adekomaya, 2024). The use of AI-driven adaptive learning platforms in diverse educational settings has shown promis- ing results in reducing achievement gaps between students from dif- ferent socio-economic backgrounds.

Finally, adaptive learning technologies promote SDG 13 (Climate Action) by integrating environmental education into personalized learning paths (Apoki et al., 2022). This fosters a generation of envi- ronmentally conscious individuals who are better equipped to under- stand and address climate change and sustainability issues. Adaptive learning platforms can include modules on climate change and sustain- ability, encouraging students to engage with and understand these critical global issues from a young age.

Figure 3 that follows shows the dynamics of the frequency of search requests using the search items “adaptive learning” and “sus- tainable education” (Figure 3). One can see that the search frequency for both terms is quite similar and both terms are often being searched simultaneously after 2013–2014. The parallel increase in search frequency for “adaptive learning” and “sustainable education” post-2014 may reflect a broader shift in educational priorities towards more personalized, technologically integrated, and long-term

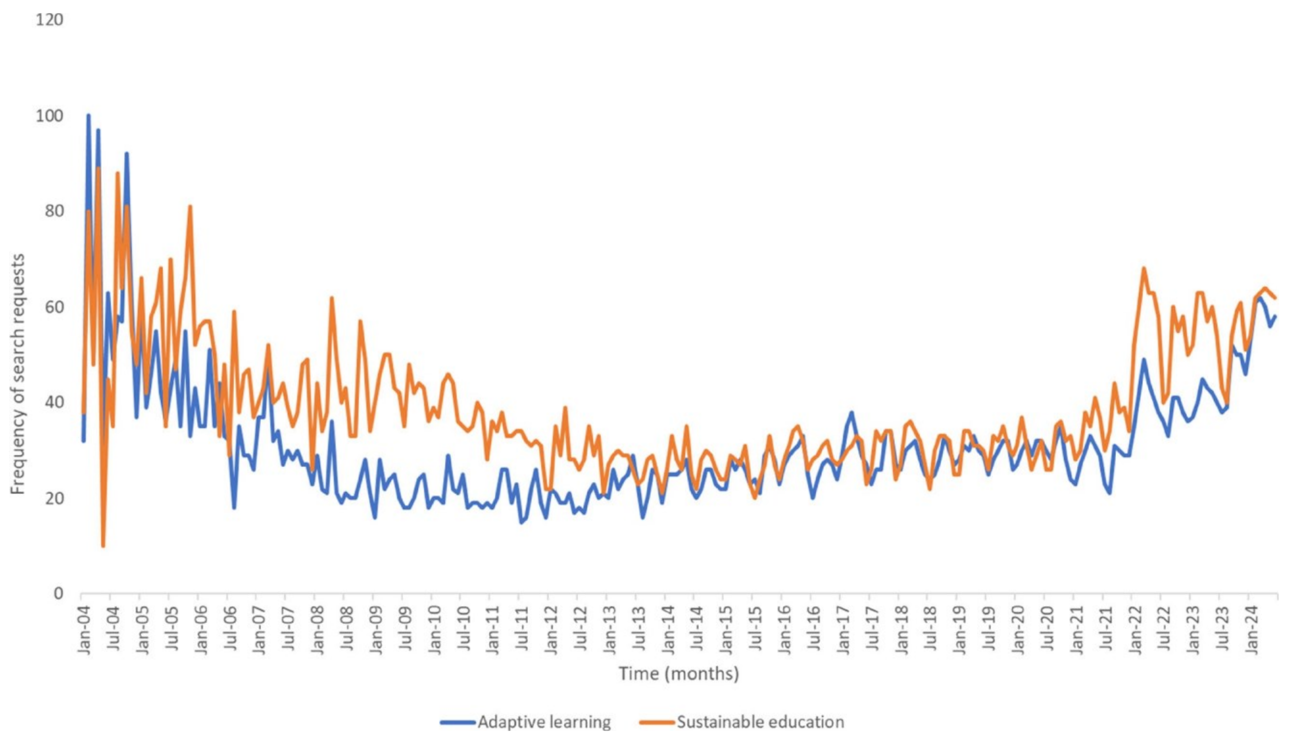


FIGURE 3 Dynamics of frequency of search of the terms of “adaptive learning” and “sustainable education” (2004–2024). *Source*: Own results based on Google Trends.

sustainable educational practices. This correlation can be attributed to several factors: (i) adaptive leaning aligns with sustainable education, which aims not only for environmental sustainability but also for sus- tainable, long-term learning strategies that benefit learners over time;
(ii) technologies used in adaptive learning align well with the principles of sustainable education, which often include the integration of tech- nological advancements to create more efficient and enduring educa- tional practices; (iii) adaptive learning and sustainable education align with global educational goals, such as the UN SDG 4; (iv) there has been a noticeable increase in research and policy development around both adaptive learning and sustainable education; (v) the education technology market's growth likely corresponds with an increased interest in sustainable education, as both areas benefit from techno- logical innovation.

Adaptive learning holds immense potential to revolutionize sus- tainable education by catering to the individual needs of learners. Firstly, it allows for personalized instruction, enabling students to learn at their own pace and style. By adapting the content, delivery, and assessment methods to suit each student's unique requirements, adaptive learning ensures a more engaging and effective learning experience (Marougkas et al., 2023). Additionally, this approach pro- motes self-directed learning as students take ownership of their edu- cation by setting goals and monitoring progress. Moreover, adaptive learning systems collect vast amounts of data on student perfor- mance, allowing educators to identify knowledge gaps and tailor inter- ventions accordingly (Currie et al., 2022). This data-driven approach empowers teachers to provide targeted support while optimizing resource allocation for a more efficient educational system that aligns with SDGs (Romanova & Kuzmin, 2021).

The implementation of adaptive learning in sustainable education brings forth a transformative approach to teaching and learning. By integrating technology, data analytics, and personalized instruction, adaptive learning empowers educators to tailor educational experi- ences according to individual needs, preferences, and learning styles. Through the utilization of intelligent algorithms, adaptive learning platforms continuously assess students' progress and adapt instruc- tional content accordingly. This personalized approach fosters greater engagement and motivation among students, leading to improved aca- demic outcomes (Aulakh et al., 2023).

Additionally, by leveraging digital resources and reducing bureau- cracy and paperwork, adaptive learning contributes to a more sustain- able educational environment. The implementation of adaptive learning also facilitates the development of lifelong learners who are equipped with the necessary skills to thrive in an ever-changing world while promoting sustainability as an integral part of their education journey (Holman & Sˇvejdarová, 2023).

Adopting adaptive learning for sustainable education presents a unique set of challenges that require innovative solutions. One major obstacle is the limited access to technology and internet connectivity in many developing regions. To overcome this, offline adaptive learn- ing platforms can be developed, allowing students to access educa- tional content without an internet connection (Tzenios, 2020). Another challenge is the lack of trained educators who can effectively implement adaptive learning strategies (Adarkwah, 2021). Addressing this issue requires comprehensive training programs and support for teachers to enhance their digital literacy skills and enable them to leverage adaptive learning tools effectively. Additionally, the high cost of implementing adaptive learning systems can hinder widespread adoption. Collaborative efforts between governments, educational institutions, and technology providers are necessary to develop affordable solutions that make adaptive learning accessible to all learners, ensuring sustainable education for future generations (Kant et al., 2021).

As technology continues to advance, the future prospects of adaptive learning in sustainable education are promising. With the ability to personalize instruction and tailor content to individual learners, adaptive learning has the potential to revolu- tionize education (Muca, Buonaiuto, et al., 2023). By leveraging data analytics and AI, educators can gain valuable insights into students' strengths and weaknesses, facilitating targeted interven- tions and personalized support (Simionescu et al., 2022). Thence, adaptive learning can promote sustainability by reducing paper waste through digital resources and fostering eco-friendly practices as well as integration for students regardless of their physical loca- tion or background.

4 | CHALLENGES IN IMPLEMENTING ADAPTIVE LEARNING TECHNOLOGIES

The integration of adaptive learning technologies into education has brought significant challenges apart from otherwise significant advancements. As educational institutions strive to revolutionize the traditional classroom experience, they must address several hurdles to ensure the successful implementation of adaptive learning technolo- gies (Sá & Serpa, 2020). However, there is always the need for contin- uous updates and maintenance of adaptive learning technologies to ensure they remain effective. These systems rely on sophisticated algorithms and large datasets that must be regularly updated to stay aligned with evolving educational standards, technological advance- ments, and changing student needs. Regular updates are essential for incorporating new content, improving personalization, fixing technical issues, and ensuring data security. Without ongoing maintenance and updates, adaptive learning technologies risk becoming outdated and less effective, which could diminish their value in educational set- tings. Institutions must therefore plan for continuous support and upgrading of these systems as part of their long-term strategy for suc- cessful implementation (Lee & Lee, 2024).

Moreover, one should not forget about the variability in technol- ogy access among different population (Major et al., 2021). The inte- gration of adaptive learning technologies and AI in education must account for disparities in technology access to ensure equitable edu- cational opportunities. In many regions, especially in developing coun- tries, limited access to reliable internet connectivity, digital devices, and technical support poses significant barriers to the effective imple- mentation of these technologies. Addressing these disparities is crucial for realizing the full potential of adaptive learning and AI in promoting inclusive and equitable education.

Another critical concern is the potential for adaptive learning technologies to contribute to widening the digital divide. While these technologies can significantly enhance educational outcomes, they may also exacerbate existing inequalities if access to them is not dis- tributed equitably (Dumont & Ready, 2023). Students from disadvan- taged backgrounds, rural areas, or lower-income families may lack the devices, internet connectivity, or digital literacy skills needed to effec- tively engage with adaptive learning tools. This lack of access could further marginalize these students, widening the gap between them and their peers who have better access to technology. To prevent this outcome, it is essential to implement strategies that promote equita- ble access to adaptive learning technologies, including infrastructure development, affordable devices, and digital literacy programs. By addressing these issues, one can ensure that adaptive learning tech- nologies help close the digital divide rather than widen it.

In addition, there are other several challenges to be considered. First, there is resistance to change from educators who are accus- tomed to conventional teaching methods and may be skeptical about the effectiveness of new technologies (Núñez-Canal et al., 2022). This resistance can be due to a lack of understanding of how these tech- nologies work or concerns about the additional time and effort required to integrate them into existing curricula. Second, the infra- structure in traditional schools may not support advanced technologi- cal tools, requiring significant investment in hardware, software, and reliable internet connectivity (e.g., in places such as some African countries) (Maphosa, 2021). Atlast, there are cultural and institutional barriers, where established educational norms and policies may not align with the flexible, personalized approaches offered by adaptive learning technologies (Ayeni et al., 2024). Addressing these challenges requires comprehensive training for educators, upgrades to infrastruc- ture, and policy adjustments to facilitate the seamless integration of adaptive learning technologies.

Another critical issue is the potential for AI bias in educational tools which arises when algorithms produce skewed results that dis- advantage certain student groups, often due to biased training data or flawed algorithm design (Ferrara, 2023). For instance, an AI system trained predominantly on data from a specific demographic may not perform equally well for students from diverse backgrounds, leading to unequal educational opportunities and outcomes. To mitigate AI bias, it is essential to ensure diverse and representative data sets, involve diverse teams in the development process, and continuously monitor and audit AI systems for biases. By implementing these mea- sures, we can help create more fair and inclusive educational environ- ments that benefit all students.

Resistance from educators and institutions is an additional common challenge in the adoption of adaptive learning technologies. Educators may resist these technologies due to a lack of familiarity, fear of obsolescence, or concerns about the time and effort required for training. Skepticism about the effectiveness of adaptive learning tools and the potential reduction in personal interaction with students can also contribute to resistance (Alzahrani et al., 2023). From an institutional perspective, concerns about the financial investment, potential disruption to established processes, and uncertainty about long-term benefits can hinder the adoption of these technologies. To address these concerns, it is crucial to provide comprehensive train- ing, clearly communicate the benefits, and involve educators in the decision-making process. By addressing resistance proactively, institu- tions can pave the way for a smoother and more successful integra- tion of adaptive learning technologies.

Furthermore, cultural differences can also significantly impact the acceptance and effectiveness of adaptive learning technologies (Essa et al., 2023). Cultural attitudes towards technology, education, and authority can shape how students, educators, and institutions per- ceive and interact with these tools. For instance, in cultures that emphasize teacher-centered instruction, there may be resistance to the more autonomous, student-centered learning models promoted by adaptive technologies. Furthermore, cultural variations in commu- nication styles, learning preferences, and the role of feedback can affect how effectively students engage with these technologies. To ensure the successful implementation of adaptive learning systems, it is crucial to consider these cultural factors and adapt the technologies to align with local educational practices and values.

In order to mitigate these challenges, it is essential to adopt strat- egies that provide offline adaptive learning solutions, ensuring that students can access educational content without continuous internet connectivity. Additionally, government and private sector partnerships can play a pivotal role in enhancing infrastructure, providing afford- able digital devices, and offering training programs for educators and students to improve digital literacy. By focusing on these measures, we can bridge the digital divide and ensure that the benefits of adap- tive learning technologies are accessible to all students, regardless of their socio-economic background or geographic location.

One of the foremost challenges is resistance to change. Educa- tional systems have been structured around traditional teaching methods for centuries, and many educators may be hesitant to embrace new technologies. Convincing teachers and administrators that adaptive learning can enhance student outcomes requires a com- prehensive approach that emphasizes its benefits, such as personal- ized instruction and improved student engagement. Another significant challenge lies in the availability and quality of digital con- tent. Adaptive learning relies heavily on content that can be tailored to each student's needs and preferences (Raj & Renumol, 2022). How- ever, creating such content demands considerable resources, exper- tise, and time. To overcome this obstacle, collaborations between content developers and educators should be fostered to ensure the creation of high-quality digital resources that align with curriculum standards (Sangiuliano Intra et al., 2023).

Additionally, one more important consideration to be considered is the potential dependency on technology that adaptive learning might create among students (Wang et al., 2023). As students become accustomed to the personalized guidance and instant feedback pro- vided by these systems, they may develop a reliance on technology that reduces their ability to engage in self-directed learning and inde- pendent problem-solving. This dependency could undermine the development of critical thinking skills, as students may struggle to manage their learning processes without the support of adaptive tech- nologies. To mitigate this risk, educators should implement strategies that promote a balanced approach, encouraging the development of autonomous learning skills alongside the use of adaptive technologies. This could include integrating traditional learning methods, fostering activities that require independent thought, and providing opportuni- ties for students to practice problem-solving without technological assistance.

In addition to these challenges, the cost implications of imple- menting adaptive learning technologies are a significant consideration. The initial investment required for software licenses, hardware upgrades, and the installation of necessary infrastructure can be sub- stantial. Ongoing costs, including software maintenance, updates, and technical support, also need to be factored into the budget (Walker et al., 2023). Moreover, training and professional development for educators represent an essential but often overlooked cost, as teachers must be adequately prepared to use adaptive learning tools effectively. The financial burden can vary depending on the size of the educational institution, the extent of existing technological infrastruc- ture, and the specific adaptive learning solutions chosen. A compre- hensive cost–benefit analysis is critical to determine whether the educational benefits of these technologies justify the investment and to ensure their sustainable implementation across diverse educational contexts.

Furthermore, there is a need for robust infrastructure and tech- nology support in educational institutions. Implementing adaptive learning technologies requires reliable internet connectivity, adequate hardware devices like computers or tablets, software compatibility across different platforms or operating systems, as well as technical support for troubleshooting issues promptly (Kesavan et al., 2022). Data privacy concerns also pose a significant challenge in implement- ing adaptive learning technologies. The collection of personal data from students raises ethical questions regarding how it will be used or shared with third parties (Jones, 2019; Lutz & Newlands, 2021). Establishing clear policies on data privacy protection and compliance with relevant regulations is essential to address these concerns effec- tively. All in all, overcoming challenges associated with resistance to change among educators, availability of quality digital content, infra- structure limitations, and data privacy concerns are crucial for their successful implementation (Ahmad, Mohd Noor, et al., 2023; Almaiah et al., 2020).

Yet another crucial element in overcoming these obstacles is the role of teacher training and professional development. Educators must be equipped with the necessary skills to effectively use adaptive learning technologies in their classrooms (Li et al., 2023). This includes understanding how to personalize learning experiences using these tools, interpreting data-driven insights to inform instruction, and con- tinuously adapting their teaching strategies. Professional development programs should be designed to provide ongoing support and training, ensuring that educators remain confident and competent in using adaptive technologies. Without adequate training, the full potential of these technologies may not be realized, limiting their impact on edu- cational outcomes.

The ability of AI and adaptive learning to personalize the learning experience based on individual needs and abilities has garnered wide- spread recognition and adoption across various educational institu- tions. One can explore some real-world case studies highlighting the success of adaptive learning in transforming education (Mian et al., 2020).

By employing the AI technology to deliver personalized instruc- tion, educators can effectively address individual student needs while fostering a deeper understanding of complex concepts across various academic disciplines.

5 | MATERIALS AND METHODS

In this section of our paper, we apply the bibliometric approach that is based on the software tool VOSviewer (Version: 1.6.18) to delineate the foundational contributions within the topic of adaptive learning and AI within the period spanning 1990 to 2023, utilizing the Web of Science (WoS) database. Bibliometrics represents a metrological approach amalgamating mathematical, statistical, and bibliographic techniques. It entails a quantitative assessment and categorization of an extensive body of scholarly work based on published texts (Adisa et al., 2002; Tao et al., 2021). Today, bibliometrics constitutes an important part of data science and is often used for the quantitative analysis of the research literature using such methods as cluster analy- sis and mapping (Sahoo, 2022; Strielkowski et al., 2022).

5.1 | Data and algorithm selection

We employed the VOSviewer software to perform the statistical ana- lyses on the publications indexed in WoS featuring such information as countries, authors, abstracts, and keywords to analyze the major research forces in AI and adaptive learning with the help of assessing the co-occurrences and keywords' cluster analyses. Table 2 that follows provides the summary of data and the algorithm for the data selection.

In addition, Figure 4 outlines the methods used in our study describing the study selection criteria and the screening process that included searching within the title, abstract and not just keywords (which is important, since some technical papers without focusing on learning, may use the keywords but might not align with the perspec- tive of this review).

5.2 | Sample of publications

We have chosen the WoS database and conducted a search using the terms “adaptive learning” and “artificial intelligence” which retrieved a total number of 3518 indexed publications (2501 articles and 762 proceeding papers among them) (see Table 2 above).

Figure 5 that follows depicts the trend of the publications on adaptive learning over time using the sample of publications from WoS database (1990–2023). We have deliberately excluded the year of 2024 in order not to bias the growing dynamics because the publi- cation count is still ongoing.

Looking at the trends shown in Figure 5, it becomes apparent that the main spike in the publications on adaptive learning and AI occurred around 2018–2019 which was further enhanced by the COVID-19 pandemic in 2020 and the rapidly growing interest and demand for everything digital applied to education that was caused by the “digital surge” that the pandemic caused.

TABLE 2 Summary of data and data selection algorithm.

Category	Specific criteria
database	
Citation indices	SCI-Expanded, SSCI
Language	“English”
Keywords	“adaptive learning” AND “artificial intelligence”
Document types:	
Articles	2501
Proceeding papers	762
Others	188
Sample size	$N = 3518$

Source: Own results.

6 | EMPIRICAL ANALYSIS: BIBLIOMETRIC APPROACH

6.1 | Data analysis: Journals, institutions, and publications

We commence our bibliographic analysis with the scrutiny of data represented by top journals publishing research on adaptive learning and AI between 1990 and 2024, as well as top prolific institutions working on these subjects. In addition, we present the most cited pub- lications on adaptive learning and AI in education and e-learning.

In order to systematically assess the effectiveness of adaptive learning strategies, it is crucial to adopt a clear framework that encom- passes multiple dimensions of evaluation. This framework should include:

1. Measure student engagement by assessing the level of student interaction with the adaptive learning platform, focusing on met- rics such as time spent on tasks, completion rates, and participa- tion in interactive elements. Higher engagement levels often correlate with better learning outcomes.
2. Assessing academic performance by measuring improvements in academic performance by comparing grades, test scores, and over- all comprehension before and after the introduction of adaptive learning technologies. This quantitative data provides a clear indi- cator of the effectiveness of the strategies.
3. Retention and application of knowledge through evaluating the long-term retention of learned material and the ability of students

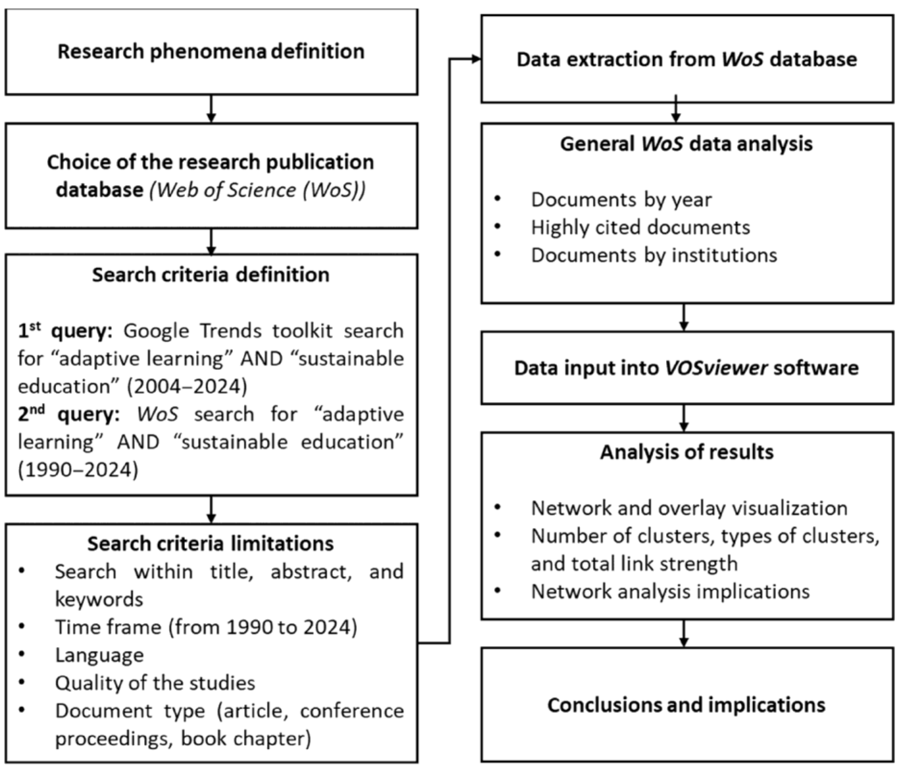


FIGURE 4 Outline of the bibliometric research methodology. *Source*: Own results.

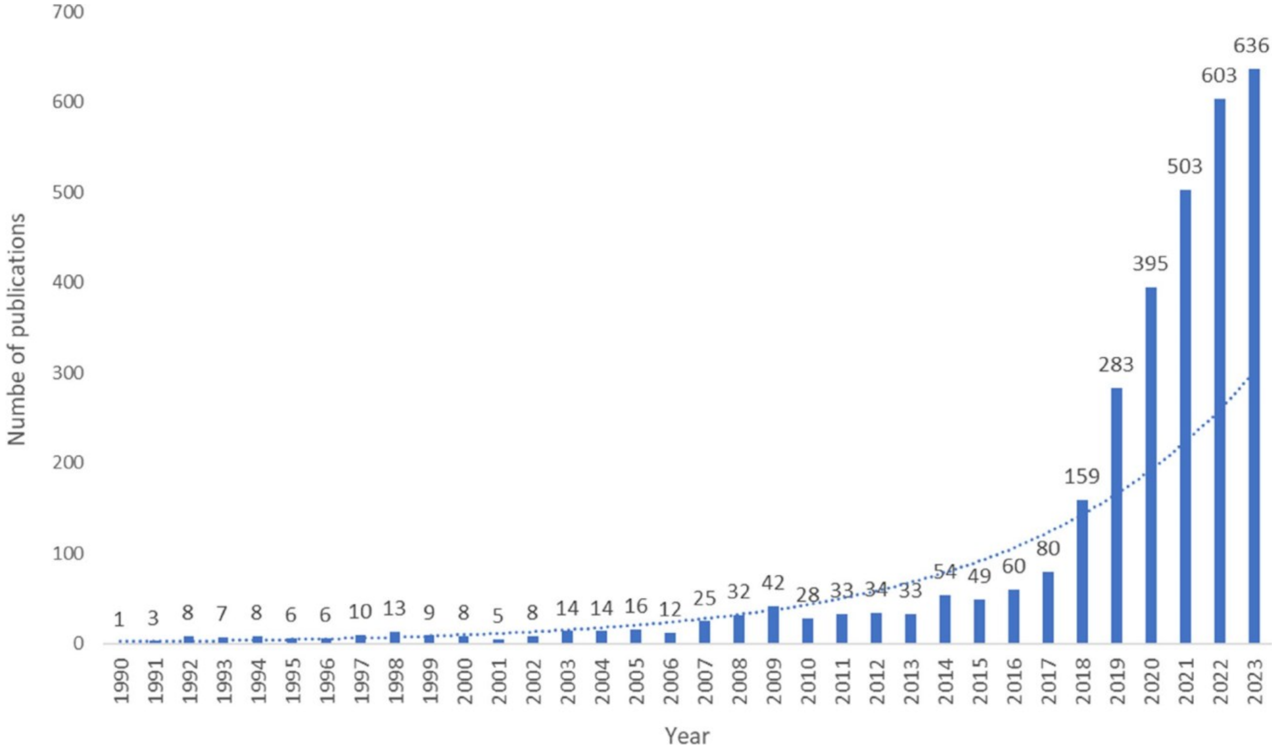


FIGURE 5 Trend of the publications on adaptive learning over time (1990–2023). *Source*: Own results.

to apply concepts in different contexts. This could involve follow- up assessments or practical applications of knowledge.

4. Studying student and teacher feedback by collect qualitative data from both students and teachers through surveys and interviews to gauge their satisfaction with the adaptive learning tools and their perceived impact on the learning process.
5. Increasing scalability and adaptability by examining how effectively the adaptive learning system can be scaled across various educa- tional settings and adapted to different curricula and student demographics.
6. Ensuring equity and inclusivity by ensuring that the adaptive learn- ing technologies promote equitable educational opportunities for all students, including those from diverse socio-economic back- grounds, and do not inadvertently contribute to widening educa- tional disparities.

By implementing this framework, educators, researchers, and pol- icymakers can systematically evaluate the success of adaptive learning strategies, ensuring that they meet their intended goals and contrib- ute positively to educational outcomes.

Figure 6 that follows offers an outline of the top 10 most prolific journals publishing articles and proceedings papers on adaptive learn- ing and AI between 1990 and 2024. One can see that the share of the journals by the new publishers is rising compared to the share of the entrenched journals published by the established publishers (see Figure 6).

Furthermore, Figure 7 provides an account of the top 10 most prolific institutions producing publications on adaptive learning and AI between 2000 and 2024. One can see very prestigious institutions such as University of London, University of California, or Chinese Academy of Sciences being among them (see Figure 7).

In addition, Table 3 provides a list of most cited publication on the topics under the investigation that has been carried out in this study (see Table 3 below).

One can observe from Table 3 that even though some of the most-cited publications are (logically) quite old and some of them are review studies, the focus that can be traced is on the e-learning and student-professor interactions in the classroom. The issues whether the teacher can be substituted by AI in the education process or what should tutors do to cope with the new challenges are also mentioned quite often.

6.2 | Text-based network analysis

Further in this sub-section, we present the results of the empirical model based on the bibliometric analyzis that employs the VOSviewer software tool. The results of the analysis are presented in the form of visual network maps that allow for deducing the key patterns and occurrences.

Figure 8 below presents the visualization of the network cluster analysis with a map based on the text data from the sample of 3518 publications indexed in WoS database from 1990 until 2024. Our results of the bibliometric network analysis demonstrate that three main clusters were identified. The analysis of using keywords and phrases in the publications retrieved from WoS revealed that the key

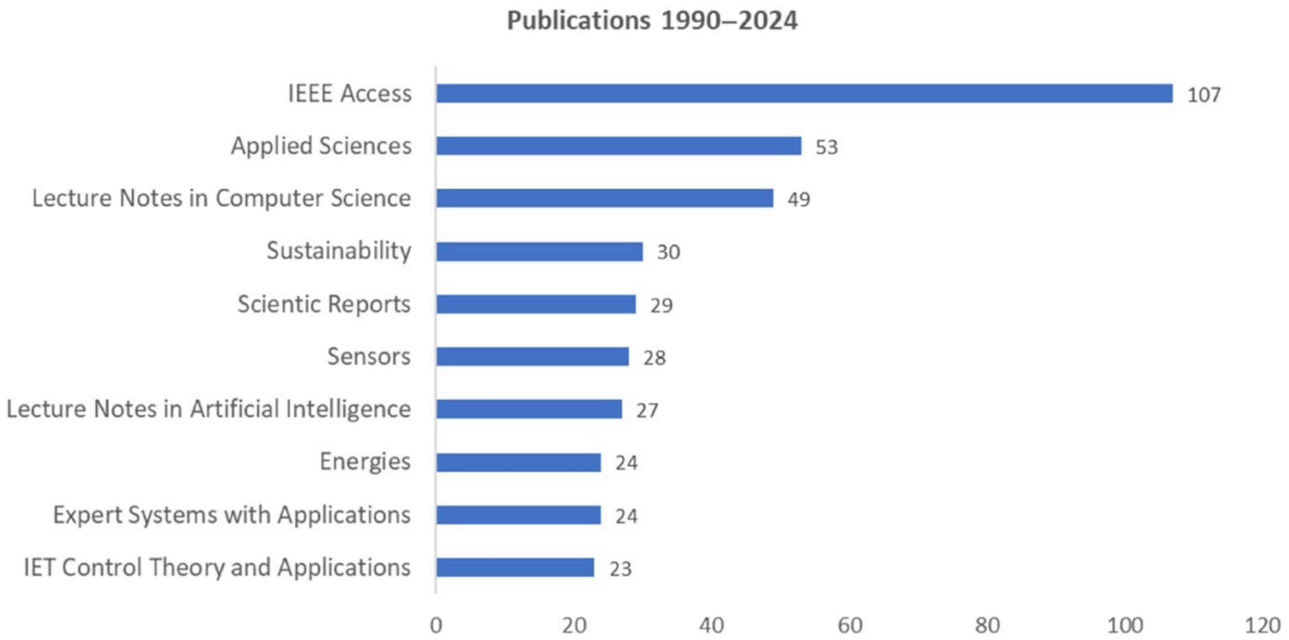


FIGURE 6 Most prolific journals (1990–2024). *Source*: Own results based on Web of Science (WoS).

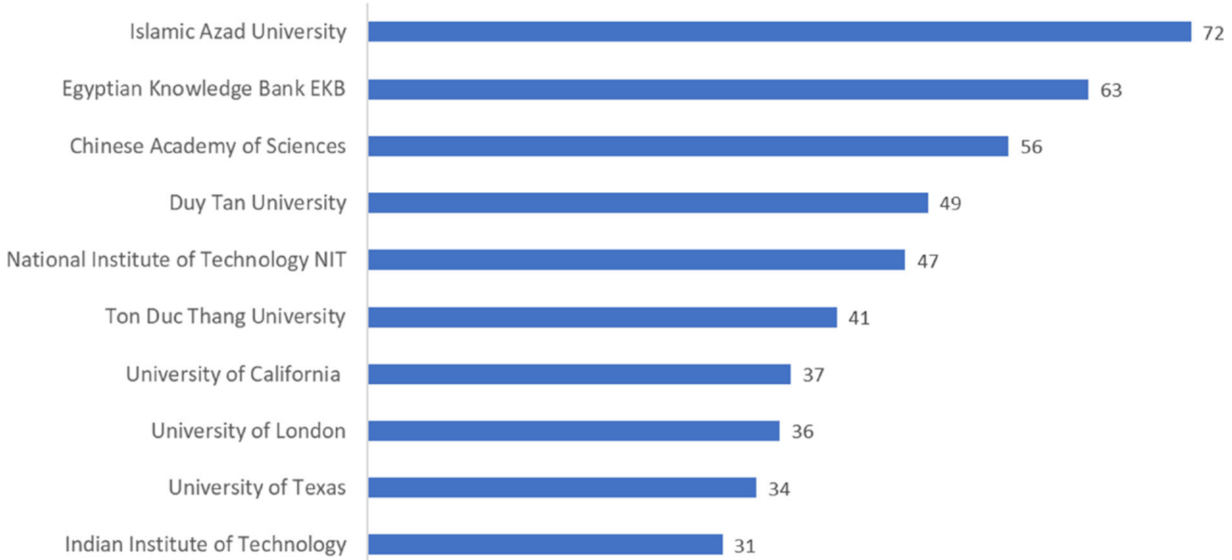


FIGURE 7 Most prolific institutions by affiliation (1990–2024). *Source*: Own results based on Web of Science (WoS).

terms connected to "adaptive learning" and "artificial intelligence" are most often associated with the following concepts: (i) Intelligence learning (Cluster 1 or red clustering); (ii) Parameter prediction (Cluster 2 or green clustering); and (iii) Dataset classification (Cluster 3 or blue color clustering).

Red clustering "intelligence learning" offers a panoramic view of the synergies between adaptive learning and AI. The cluster analysis reveals intricate connections between various thematic elements, showcasing their symbiotic relationship and illuminating the multiface- ted dimensions underpinning the advancement of these domains. Within this cluster, keywords such as "intelligence" and "learning" stand as linchpins, anchoring diverse sub-themes like "technology," "learner," "adaptation," and "environment."

The analysis of the "intelligence learning" cluster elucidates sev- eral significant themes. The integration of AI technology into adaptive learning settings underscores the transformative potential to create intelligent learning environments. As Grassini (Grassini, 2023) points out this convergence facilitates personalized instruction, adapting content and delivery methods to meet individual learner preferences and needs. Moreover, the analysis highlights the centrality of "interaction" and "user" elements, accentuating the importance of human-computer interaction and user-centric design in optimizing the

TABLE 3 Top 10 most cited articles (1990–2024).

Authors	Title	Number of citations
Zawacki-Richter et al. (2019)	Systematic review of research on AI applications in higher education–where are the educators?	[illegible]
Xie et al. (2019)	Trends and development in technology-enhanced adaptive/ personalized learning: A systematic review of journal publications from 2007 to 2017	205
Magnisalis et al. (2011)	Adaptive and intelligent systems for collaborative learning support: a review of the field	127
Mousavinasab et al. (2021)	Intelligent tutoring systems: a systematic review of characteristics, applications, and evaluation methods	119
Almohammad et al. (2017)	A survey of artificial intelligence techniques employed for adaptive educational systems within e-learning platforms	101
Tang et al. (2023)	Trends in artificial intelligence-supported e-learning: a systematic review and co-citation network analysis (1998–2019)	88
Zhai et al. (2021)	A review of Artificial Intelligence (AI) in education from 2010 to 2020	83
Ciolacu et al. (2018)	Education 4.0-Artificial Intelligence assisted higher education: early recognition system with machine learning to support students' success	57
	online teacher in future education	
Tsai et al. (2020)	Precision education with statistical learning and deep learning: a case study in Taiwan	44

Source: Own results based on Web of Science database (Zhai et al., 2021; Ally, 2019; Almohammad et al., 2017; Ciolacu et al., 2018; Magnisalis et al., 2011; Mousavinasab et al., 2021; Tang et al., 2023; Tsai et al., 2020; Xie et al., 2019; Zawacki-Richter et al., 2019).

learning experience, as for example explained in the literature by Smith (Smith, 2022).

Another prominent theme steps into to the dynamic interplay between learners and their environment. The cluster underscores the role of "adaptation" as a cornerstone, where AI-driven systems dynamically adjust the learning environment in response to learner progress and per- formance. As Kadaruddin (Kadaruddin, 2023) explains in relation to this finding, this dynamic adaptability enhances learner engagement and pro- motes optimal knowledge retention. Concurrently, the notion of "chal- lenge" also emerges as a critical factor in the literature, as AI-enabled learning environments strategically calibrate challenges to match learners' cognitive capacities, stimulating intellectual growth while preventing cog- nitive overload (Ahmad, Alam, et al., 2023; Huynh-The et al., 2022).

Thence, the "intelligence learning" cluster underscores the trans- formative potential of AI-powered adaptive learning environments. By leveraging cutting-edge AI technologies, educational paradigms are shifting towards learner-centric models that promote tailored instruc- tion and dynamic adaptation. The synthesis of research within this cluster underscores the need for an ecosystem that harmonizes tech- nology, environment, and learner interactions, ushering in a new era of intelligent, adaptable, and challenging learning experiences. The implications of this synthesis extend to pedagogical design, curricular development, and the continuous evolution of AI-augmented educa- tion (Garzón, 2021; Matthew et al., 2021).

Figure 9 that follows confirms the discussion above by offering the density visualization of the network cluster analysis map. It pro- vides the density level of the topics of adaptive learning and AI based on the quantity and depth of research (the thicker the density color, the more research was recorded and documented on this topic or concept) (see Figure 9).

Green clustering "parameter prediction" includes the ideas that elucidate the interplay between adaptive learning and AI-driven pre- dictive models. This cluster analysis underscores the intricate bonds that connect the diverse themes and concepts interwoven by the cluster's key keywords. Among these, "prediction" and "parameter" stand as pivotal nodes, intricately linked with concepts such as "value," "estimation," and advanced methodologies like "artificial neu- ral network" and "adaptive neuro fuzzy inference."

The analysis of the "parameter prediction" cluster unfurls several prominent themes. Central to these themes is the concept of predic- tive modeling, where the AI is utilized to anticipate future values or conditions based on historical data and relevant parameters (Yun et al., 2022). The integration of "artificial neural networks" and "adap- tive neuro fuzzy inference" emerges as a potent avenue for enhancing predictive accuracy and generalization. According to some authors, these advanced techniques demonstrate their efficiency in refining parameter estimation and forecasting, presenting promising opportu- nities for educational applications (Rahman et al., 2021).

Within this cluster, the concept of "indicator" assumes significance as a tool for monitoring and measuring predictive accuracy. The incor- poration of indicators allows researchers and practitioners to assess the performance of predictive models and gauge their efficacy in diverse adaptive learning contexts. This underlines the importance of robust evaluation methodologies to ensure the reliability and applicability of predictive models within educational settings (Zhong et al., 2021).

The synthesis of research within the "parameter prediction" clus- ter underscores the transformative potential of predictive modeling in adaptive learning. By utilizing AI-powered techniques, educators can anticipate learners' future performance, needs, and progress, thereby tailoring instruction and interventions. The convergence of "parame- ter prediction" techniques with adaptive learning holds the promise of enhancing personalized education, optimizing learning outcomes, and fostering efficient resource allocation (Delgado et al., 2020).

The implications of this synthesis extend to pedagogical design, assessment strategies, and policy-making. The integration of predic- tive models calls for a holistic approach that combines sound educa- tional theory with cutting-edge AI methodologies (Kubsch et al., 2023). Moreover, this synthesis underscores the need for

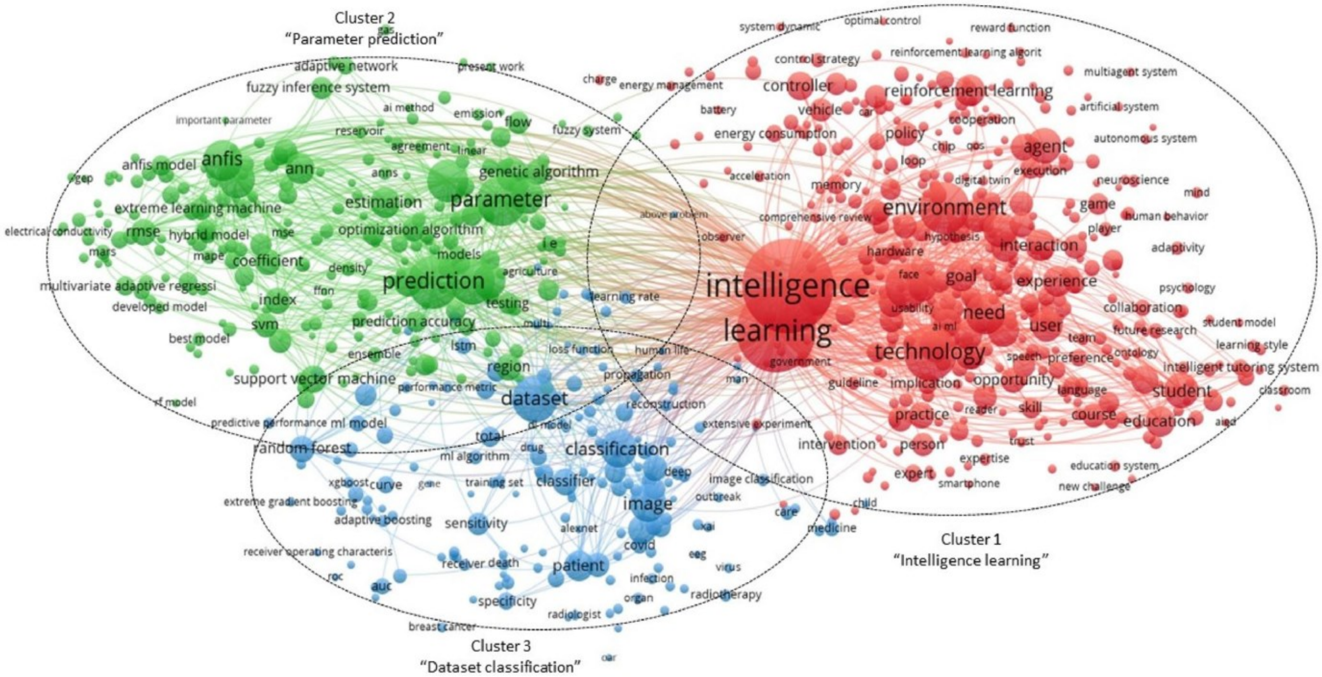


FIGURE 8 The dominant clusters of cross-sector research connected with adaptive learning and artificial intelligence retrieved from the sample of 3518 publications indexed in Web of Science (WoS). *Source*: Own results based on VOSViewer v. 1.6.18 software.

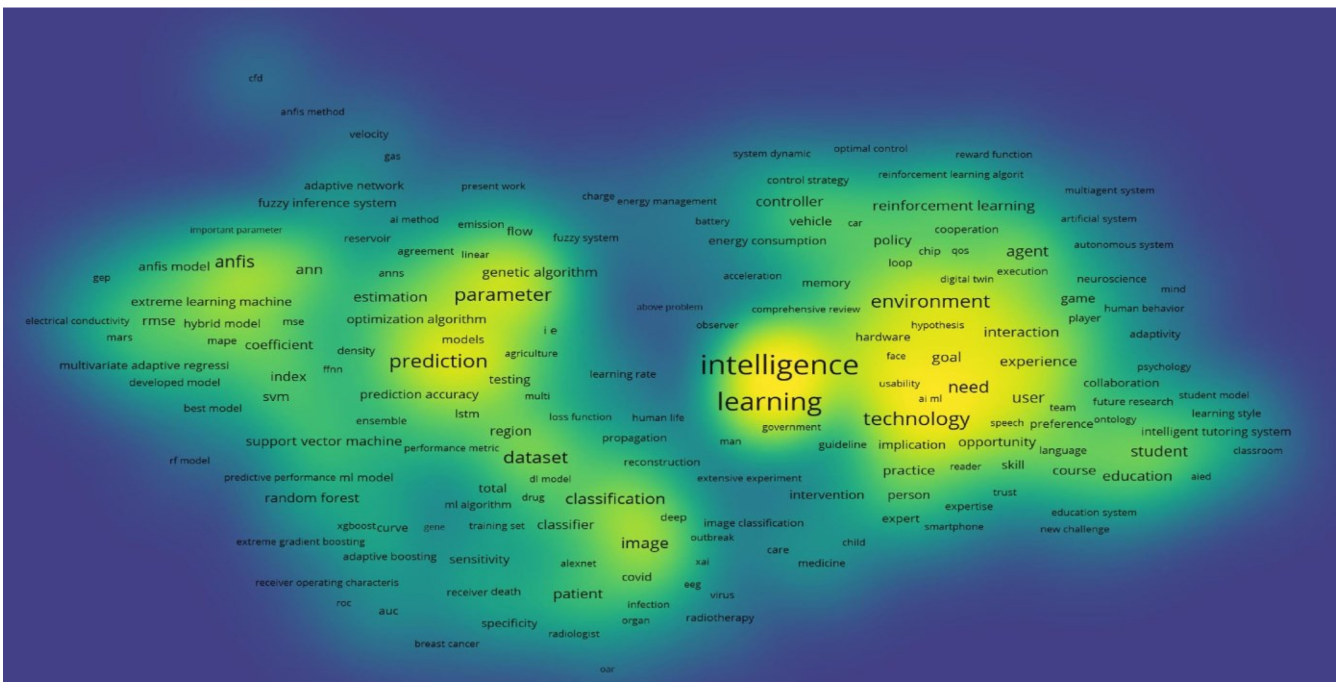


FIGURE 9 Density visualization of the network cluster analysis of the sample of 3518 publications on adaptive learning and artificial intelligence indexed in Web of Science (WoS). *Source*: Own results based on VOSViewer v. 1.6.18 software.

continued interdisciplinary collaboration, where educators, researchers, and AI practitioners converge to enhance the sophistica- tion and applicability of parameter prediction within adaptive learning contexts (Crompton & Burke, 2023).

Finally, the blue cluster "dataset classification" encompasses a diverse range of research themes, offering a panoramic view of the interplay between adaptive learning and AI-driven dataset classifica- tion methodologies. This cluster analysis highlights the intricate network of connections binding together various sub-themes and concepts, with focal points on “classification,” “score,” “dataset,” and methodologies such as “deep learning model” and “classifier.”

Analysis of the “dataset classification” cluster reveals several piv- otal themes. Central among these is the utilization of classification methodologies to discern patterns and relationships within complex datasets. The integration of “deep learning models” and “classifiers” emerges as a potent avenue for enhancing classification accuracy, par- ticularly in tasks related to image and data analysis. This cluster under- scores the paramount importance of robust evaluation metrics, such as “score,” which enable researchers to quantify and compare the effi- cacy of different classification algorithms and models (Hazra et al., 2023).

The concept of “sensitivity” assumes significance within this clus- ter, underlining the necessity of models that can effectively capture subtle variations and nuances within datasets. The utilization of AI- driven “prediction models” within dataset classification is showcased as a powerful tool for anticipating outcomes and trends within educa- tional contexts, allowing for data-informed decision-making and per- sonalized instructional design (Caspari-Sadeghi, 2023).

The synthesis of research within the “dataset classification” clus- ter underscores the transformative potential of AI-driven classification methodologies within adaptive learning. The integration of sophisti- cated classification techniques empowers educators to categorize and analyze complex datasets, facilitating data-driven insights and inter- ventions. The interplay between “dataset classification” and adaptive learning holds promise for personalized instruction, targeted interven- tions, and the optimization of learning experiences.

The implications of this synthesis extend to educational practice, research methodologies, and technological innovation. The amalgam- ation of dataset classification with adaptive learning necessitates a holistic approach that combines pedagogical insights with advanced AI techniques. Furthermore, interdisciplinary collaboration between educators, researchers, and AI practitioners is essential to ensure the refinement and application of dataset classification methodologies within adaptive learning scenarios (Minn, 2020).

6.3 | Bibliographic network analysis

Furthermore, Figure 10 reveals the results of the network map based on the bibliographic data (keyword co-occurrences, citation, and bib- liographic coupling).

It is clear from Figure 10 that AI (depicted in red clustering) and machine learning (blue clustering) are mentioned in the research litera- ture as the key methods of prediction, detection, and two-way com- munications for organizing e-learning (red clustering) with the help of neural networks (blue clustering).

AI and ML found an array of usages in education, especially when it comes to prediction, detection, and facilitating interactions in adap- tive learning and e-learning. Additionally, the symbiotic integration of AI, ML, and neural networks fostered the evolution of predictive modeling, anomaly detection, and interactive learning interfaces within adaptive learning and e-learning environments. These technol- ogies redefined the boundaries of personalized education, offering tai- lored support, real-time interactions, and comprehensive feedback. As the educational landscape continues to evolve, the fusion of AI, ML, and neural networks promises to remain a transformative force, shap- ing the future of adaptive learning and e-learning paradigms. Through interdisciplinary collaboration and innovative research, this neural network-powered paradigm holds the potential to unlock new dimen- sions of effective and engaging educational experiences.

In summary, through the use of cluster analyses conducted in this section, it becomes evident that AI technology holds substantial importance in the context of adaptive learning, and the introduction of novel AI advancements contributes to the emergence of excep- tional scholarly investigations. Through the process of keyword clus- tering, the foundational technological underpinnings and shared application contexts within the domain of adaptive learning can be delineated. Undoubtedly, the ongoing progression and integration of nascent technologies have significantly augmented both the scope and intricacy of potential scenarios for adaptive learning applications, progressively assuming a pivotal role in propelling advancements within this discipline.

Our results address the research questions comprehensively by demonstrating the transformative potential of AI-powered adaptive learning, acknowledging associated challenges, and indicating key trends and directions for future research and policy development in sustainable adaptive education. These results offer a forward-looking perspective, aligning the study's findings with the broader vision of personalized, ethical, and engaging education facilitated by AI and adaptive learning technologies.

7 | DISCUSSION OF RESULTS

Thus, as technology continues to evolve, further exploration and interdisciplinary collaborations hold the key to unlocking the full potential of AI-augmented adaptive learning for learners, educators, and researchers alike. When it comes to tackling RQ1, our results demonstrate that adaptive learning technologies, powered by AI, are transforming education fundamentally (Cheung et al., 2021; Ouyang & Jiao, 2021). They emphasize the personalization of education through tailored content delivery, pacing adjustments, real-time feedback, and intelligent algorithms. The integration of VR technology in classrooms, guided by AI, is highlighted as a groundbreaking advancement. These advancements underline how AI and adaptive learning are shaping the future of education, aligning with the vision of sustainable education through personalized, engaging, and experiential learning (George & Wooden, 2023; Kabudi et al., 2021; Sharma et al., 2021).

In order to fully understand the impact of adaptive learning technologies, it is crucial to incorporate feedback from students and educators who have directly experienced these systems. Student feedback can reveal how these technologies influence engagement, motivation, and learning outcomes, while educators can provide insights into the practical challenges of integrating adaptive tools into

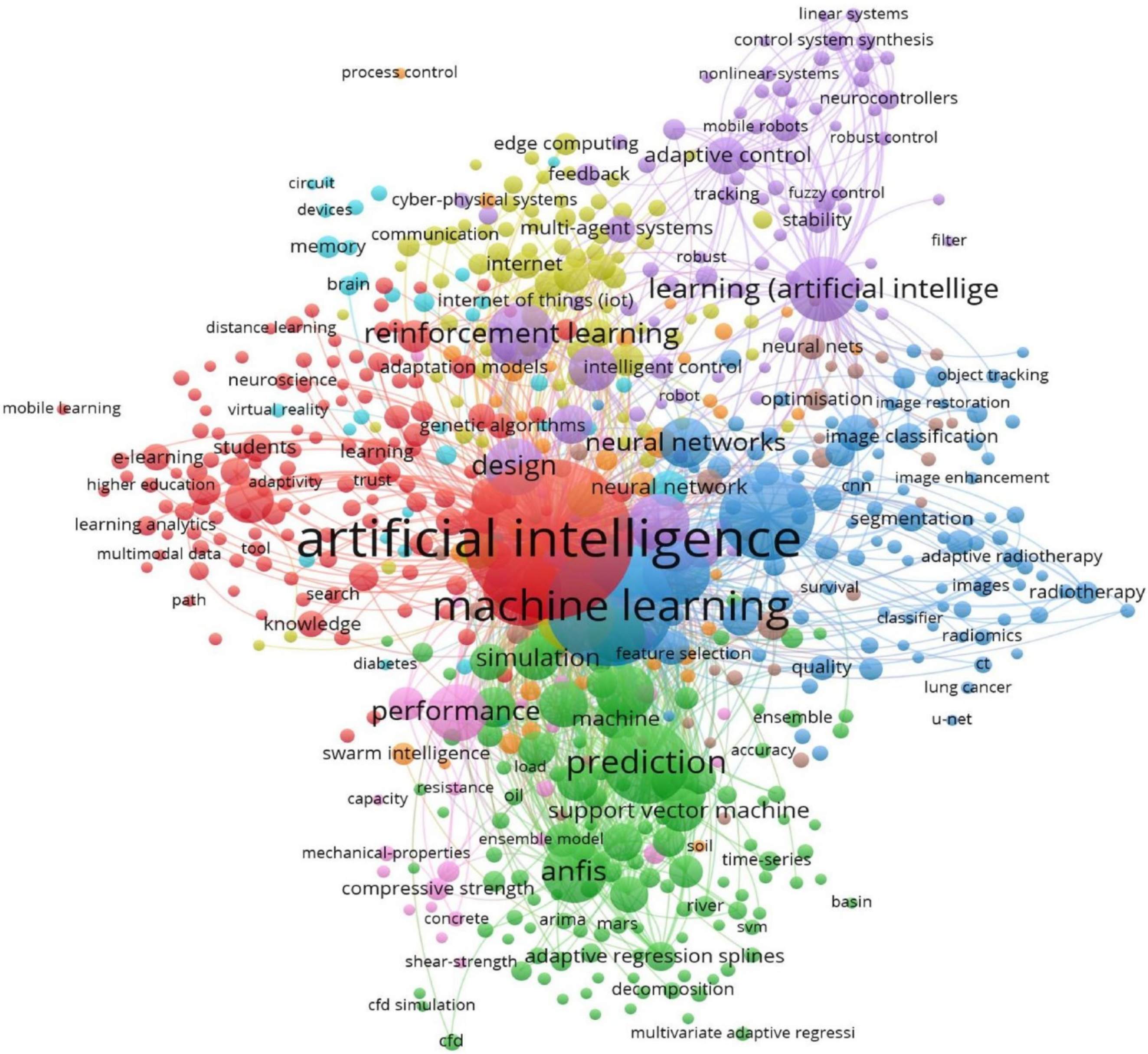


FIGURE 10 Network map based on the bibliographic data of the sample of papers containing the keywords "adaptive learning" and "artificial intelligence" retrieved from the sample of 3518 publications indexed in Web of Science (WoS). *Source*: Own results based on VOSViewer v. 1.6.18 software.

traditional classroom settings (Cavanagh et al., 2020). This real-world feedback is invaluable for validating the theoretical benefits of adap- tive learning technologies and identifying areas where further refine- ment is needed to better meet the needs of all users. By including the voices of those who interact with these technologies daily, we can ensure that adaptive learning systems are effectively tailored to enhance educational experiences across diverse contexts.

However, it is essential to acknowledge the limitations and chal- lenges associated with these technologies. Implementing adaptive learning technologies can be costly, requiring significant investments in infrastructure, training, and ongoing maintenance. Data privacy and security are major concerns, as sensitive student information must be protected from breaches. Ethical considerations regarding AI decision-making in education also need to be addressed, ensuring that algorithms do not reinforce existing biases or produce unintended negative outcomes (Khreisat et al., 2024). The effectiveness of these technologies heavily depends on the quality of data and algorithms used, which can vary widely. Educators and policymakers must navi- gate these challenges to ensure the equitable, ethical, and effective deployment of adaptive learning technologies.

Long-term effectiveness of adaptive learning technologies on stu- dent outcomes is a critical area of investigation. Some studies demon- strated that these technologies not only improve immediate academic performance by providing personalized and adaptive learning experi- ences but also have a lasting impact on students' ability to retain and apply knowledge. Over time, students who engage with adaptive learning technologies often exhibit higher levels of engagement and motivation, which contributes to better educational outcomes (Yang et al., 2022). Furthermore, adaptive learning technologies help develop critical thinking and problem-solving skills by offering tailored challenges and feedback, preparing students for future educational and career success. However, to fully understand the long-term bene- fits, continuous research and longitudinal studies are necessary to track student progress and outcomes over extended periods.

In addition, it is also important to consider the psychological impacts of personalized learning approaches on students (Shemshack & Spector, 2020). While personalized learning can enhance motivation and engagement by allowing students to work at their own pace and focus on areas where they need the most support, it can also have potential negative effects. The constant monitoring and feedback inherent in adaptive learning systems may lead to increased pressure and anxiety for some students. Moreover, if the learning experience becomes too individualized, students may feel iso- lated or miss out on valuable peer interactions that contribute to their social and emotional development. To maximize the benefits of per- sonalized learning, educators must be mindful of these psychological impacts and take steps to create a supportive and balanced learning environment.

When addressing RQ2, the challenges associated with imple- menting adaptive learning technologies, represent privacy concerns or ethical implications of AI algorithms. The authors recognize the need for policies and ethical standards focusing on data privacy, security, and AI deployment which is also reflected in the current research literature (Borenstein & Howard, 2021; Flores-Vivar & García- Peñalvo, 2023; Holmes et al., 2021). Our study emphasizes the impor- tance of balancing personalized learning experiences with safeguard- ing sensitive student information. It also highlights the importance of equitable access, emphasizing the necessity for all students, regardless of socioeconomic background, to benefit from AI-driven educational opportunities just as other relevant studies in this field (Chan, 2023; Roshanaei et al., 2023).

Finally, the question posed in RQ3 can be answered by offering an interplay between predictive modeling, parameter estimation, and adaptive learning. Our results emphasize that as adaptive learning sys- tems mature alongside AI technology, there is a tremendous potential to transform education, which is in accord with the outcomes of the relevant studies in this field (Alenezi, 2021; Troussas et al., 2022; Val- dés & Cerdá Suárez, 2021).

All of the above significantly contributes to the understanding of the transformative role of AI and adaptive learning technologies in education. Our analysis underscores that these technologies not only personalize learning but also align with the broader goals of sustain- able education, particularly in the post-COVID era (Deroncele-Acosta et al., 2023; Whalley et al., 2021). This alignment is evidenced by the tailored content delivery and real-time feedback mechanisms, which are instrumental in creating a more dynamic and responsive educa- tional environment (Liu & Yu, 2023). However, the challenges identi- fied, particularly concerning data privacy and ethical AI usage, highlight the need for a comprehensive policy framework that ensures the safe and equitable implementation of these technologies. The insights gained from the bibliometric analysis underscore the evolving nature of this field and point towards predictive modeling and param- eter estimation as key areas for future research (Dogan et al., 2023; Luan et al., 2020). These findings not only echo the existing litera- ture's emphasis on the need for ethical AI but also pave the way for policy development that could shape the future landscape of sustain- able adaptive education. The potential of AI in revolutionizing educa- tion, as revealed by this study, underscores the importance of addressing these challenges to fully harness the benefits of technology-driven educational models (Adiguzel et al., 2023; Liu et al., 2023).

Nevertheless, however promising all of these technological advancements in education may be, it is crucial to address concerns around privacy protection and ethical use of data in educational set- tings involving AI (Dhirani et al., 2023; Kooli, 2023; Marshall et al., 2022). Striking a balance between personalization and safe- guarding privacy will be essential as we navigate this new era in edu- cation (Hagadone-Bedir et al., 2023; Raj & Renumol, 2022). It becomes apparent that as adaptive learning systems continue to mature alongside advancements in AI technology, the future holds tremendous potential for transforming education as we know it today.

8 | CONCLUSIONS

Overall, our results reveal the transformative potential of AI-powered parameter prediction techniques in shaping the future of education. With the further enhancement of the adaptive learning, the integra- tion of predictive models emerges as a potent tool for tackling the power of AI to optimize and tailor educational experiences for learners around the world. The intricate dynamics between classifica- tion methodologies, dataset analysis, and adaptive learning offer a potent avenue for further implementing AI for enhancing education, optimize learning experiences, and pave the way for data-informed educational transformations led by the policy-makers and stake- holders in the field of education.

Furthermore, it becomes clear that nowadays adaptive learning represents a groundbreaking approach in personalized education that make a good use of the power of technology and AI to optimize learn- ing experiences for individual students. By leveraging data-driven insights and intelligent algorithms, adaptive systems offer tailored content delivery, pacing adjustments, and real-time feedback that enhance both students' engagements and achievements. As this revo- lution in education continues to unfold, the potential for adaptive learning to transform traditional classroom practices remains immense.

As we witness the rapid rise of adaptive learning and AI in educa- tion, it becomes apparent that the future of education will be signifi- cantly shaped by these technologies. With their ability to personalize learning experiences, offer real-time feedback, and provide targeted support, AI-powered tools hold immense potential to revolutionize education in the coming years. One key aspect of the future of educa- tion lies in the creation of personalized learning paths for students. By leveraging AI algorithms and adaptive learning platforms, educators can tailor educational content and experiences to match each stu- dent's unique needs, abilities, and interests. Furthermore, AI can greatly enhance assessment methods by providing more accurate and comprehensive evaluations.

Traditional exams often fall short in measuring a student's true understanding and mastery of a subject. However, with machine learning algorithms analyzing vast amounts of data collected from var- ious sources like quizzes, assignments, discussions, or even facial expressions during online classes, educators can gain deeper insights into students' progress and adapt teaching strategies accordingly. Another exciting prospect is the integration of VR and AR technology into classrooms. VR can create immersive environments that simulate real-world scenarios or historical events. Combined with AI-driven adaptive learning systems that adjust content based on individual stu- dent reactions or performance metrics gathered within VR simulations—students will have unprecedented opportunities for experiential learning. This is becoming a particularly interesting field for exploring and experimenting given the recent presentation of Apple Visio Pro, an AR headset created by Apple in 2023 that offers an immersive working experience but without having to be locked in the VR settings. The headset which opens up the new era of the so-called “spatial computing” (the next logical step after personal computing and mobile computing) will be on sale starting from the beginning of 2024 with a promise of unimaginable learning and pre- senting solutions it might deliver for sustainable education.

9 | PRACTICAL IMPLICATIONS, LIMITATIONS, AND PATHWAYS FOR FURTHER RESEARCH

When it comes to the practical implications of our research, it is quite apparent that the ascent of adaptive learning and AI technologies in education offers a paradigm shift, necessitating careful policy consid- erations. As these technologies take center stage, policymakers must contemplate a holistic framework that encourages the responsible integration of AI into educational practices. The development of guidelines and ethical standards for data privacy, security, and AI deployment in educational settings is imperative. Striking a balance between personalized learning experiences and safeguarding students' sensitive information is a paramount concern. Relevant government policies should also encompass the equitable distribution of AI-driven tools, ensuring that all students, regardless of socioeconomic back- ground, have access to transformative educational opportunities.

Additionally, parental involvement also appears to be crucial in enhancing the effectiveness of adaptive learning technologies. When parents actively engage in their child's learning process, they can rein- force the personalized strategies provided by these technologies. By monitoring progress, offering encouragement, and creating a support- ive learning environment at home, parents help ensure that adaptive learning tools are used effectively and consistently. Additionally, active parental involvement facilitates better communication between home and school, allowing for a more coordinated approach to addressing individual learning needs. Therefore, fostering parental involvement should be considered an integral component of imple- menting adaptive learning technologies, as it significantly contributes to the overall success and effectiveness of these tools.

One of the primary ethical concerns that also need to be dis- cussed with regard to the adaptive learning technologies is the issue of privacy and data security. AI systems often require access to large amounts of personal data to function effectively, which raises ques- tions about how this data is collected, stored, and used. Ensuring that students' privacy is protected and that data is securely managed is essential. Another ethical issue is algorithmic bias, where AI systems can inadvertently perpetuate or exacerbate existing inequalities if they are trained on biased data. It is crucial to implement safeguards and regular audits to detect and mitigate such biases. Transparency in AI decision-making processes is also important, as educators and stu- dents need to understand how AI systems arrive at their decisions. Additionally, the increasing reliance on AI in education could reduce the role of human educators, potentially impacting the development of social and emotional skills in students. To address these concerns, ethical guidelines and policies must be established to govern the use of AI in education, ensuring that these technologies are used in ways that are fair, transparent, and inclusive.

As far as the limitations of our study are concerned, several aspects need to be acknowledged. The study predominantly focuses on the broad implications of AI and adaptive learning without focusing deeply on the specific cultural, contextual, or socioeconomic nuances that could impact the adoption and effectiveness of these technolo- gies. Moreover, the study's scope is primarily rooted in the biblio- metric analysis based on the data from WoS, and its findings are contingent on the available research literature up to the knowledge cutoff date. Thence, the study might be not very efficient in capturing the recent developments or emerging trends in the field. Moreover, using publications from other databases (such as Scopus, Google Scholar, ResearchGate, or Dimensions) might also yield better and more holistic results. These databases predominantly index journals and publications that are in English and from Western countries, potentially excluding significant research published in other languages or regions. Furthermore, they may not cover all relevant conference proceedings, books, or publications in non-indexed journals, which could lead to a bias in the analysis. As a result, the findings may not fully capture the global scope of research on adaptive learning tech- nologies, and there could be an overrepresentation of certain types of studies or research from specific regions. Acknowledging these limitations is crucial for interpreting the results of the bibliometric analysis within the context of the broader literature.

Furthermore, one needs to realize that while bibliometric analysis provides valuable insights into research trends, influential publica- tions, and key contributors in the field of educational technologies, it has certain limitations. Bibliometric data is often limited to indexed journals and may not capture relevant work published in non-indexed sources, conference proceedings, or emerging online platforms. Addi- tionally, bibliometric analysis primarily focuses on quantitative mea- sures such as citation counts, which may not fully reflect the quality, impact, or practical relevance of the research. Furthermore, this method can overlook the context and content of the studies, leading to an incomplete understanding of how adaptive learning technologies are implemented and evaluated in diverse educational settings.

As far as the pathways for further research are concerned, the creation of personalized learning pathways using AI algorithms and adaptive learning platforms presents an interesting topic for further exploration and studying. Extending beyond content delivery, researchers could plunge into the creation of AI-enhanced assessment methods that provide comprehensive evaluations of student under- standing and progress. Additionally, the integration of VR technology within AI-driven adaptive learning systems presents an intriguing prospect for immersive experiential learning. Exploring the interplay between VR, AI, and adaptive learning could uncover new dimensions of educational engagement and comprehension.

Additionally, another interesting topic related to adaptive learning and AI involves the ethical use of data and privacy protection of teachers, learners, and students. Addressing concerns surrounding data privacy in AI-powered educational environments is of immense importance. Researchers in education should collaborate with policy- makers to establish ethical guidelines that balance the potential bene- fits of AI with students' privacy rights and to ensure the protection of data as well as be prepared for the scenarios involving cybercrime and data breaches.

ACKNOWLEDGMENT

Open access publishing facilitated by Ceska Zemedelska Univerzita v Praze, as part of the Wiley - CzechELib agreement.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

ORCID

Wadim Strielkowski https://orcid.org/0000-0001-6113-3841

REFERENCES

Adarkwah, M. A. (2021). "I'm not against online teaching, but what about us?": ICT in Ghana post Covid-19. *Education and Information Tec- hnologies*, *26*(2), 1665–1685. https://doi.org/10.1007/s10639-020- 10331-z

Adiguzel, T., Kaya, M. H., & Cansu, F. K. (2023). Revolutionizing education with AI: Exploring the transformative potential of ChatGPT. *Contempo- rary Educational Technology*, *15*(3), ep429. https://doi.org/10.30935/ cedtech/13152

Adisa, O. M., Masinde, M., Botai, J. O., & Botai, C. M. (2002). Bibliometric analysis of methods and tools for drought monitoring and prediction in Africa. *Sustainability*, *12*(16), 6516. https://doi.org/10.3390/ su12166516

Ahmad, S., Mohd Noor, A. S., Alwan, A. A., Gulzar, Y., Khan, W. Z., & Reegu, F. A. (2023). eLearning acceptance and adoption challenges in higher education. *Sustainability*, *15*(7), 6190. https://doi.org/10.3390/ su15076190

Ahmad, S. F., Alam, M. M., Rahmat, M. K., Shahid, M. K., Aslam, M., Salim, N. A., & Al-Abyadh, M. H. A. (2023). Leading edge or bleeding edge: Designing a framework for the adoption of AI Technology in an Educational Organization. *Sustainability*, *15*(8), 6540. https://doi.org/ 10.3390/su15086540

Akgun, S., & Greenhow, C. (2022). Artificial intelligence in education: Addressing ethical challenges in K-12 settings. *AI and Ethics*, *2*(3), 431–440. https://doi.org/10.1007/s43681-021-00096-7

Akour, M., & Alenezi, M. (2022). Higher education future in the era of digi- tal transformation. *Education Sciences*, *12*(11), 784. https://doi.org/10. 3390/educsci12110784

Alamri, H. A., Watson, S., & Watson, W. (2021). Learning technology models that support personalization within blended learning environ- ments in higher education. *TechTrends*, *65*, 62–78. https://doi.org/10. 1007/s11528-020-00530-3

Alashhab, Z. R., Anbar, M., Singh, M. M., Leau, Y. B., Al-Sai, Z. A., & Alhayja'a, S. A. (2021). Impact of coronavirus pandemic crisis on tech- nologies and cloud computing applications. *Journal of Electronic Science and Technology*, *19*(1), 100059. https://doi.org/10.1016/j.jnlest.2020. 100059

Alenezi, M. (2021). Deep dive into digital transformation in higher educa- tion institutions. *Education Sciences*, *11*(12), 770. https://doi.org/10. 3390/educsci11120770

Alenezi, M. (2023). Digital learning and digital institution in higher educa- tion. *Education Sciences*, *13*(1), 88. https://doi.org/10.3390/ educsci13010088

Ally, M. (2019). Competency profile of the digital and online teacher in future education. *The International Review of Research in Open and Dis- tance Learning*, *20*(2), 302–318. https://doi.org/10.19173/irrodl.v20i2. 4206

Almaiah, M. A., Al-Khasawneh, A., & Althunibat, A. (2020). Exploring the critical challenges and factors influencing the E-learning system usage during COVID-19 pandemic. *Education and Information Technologies*, *25*, 5261–5280. https://doi.org/10.1007/s10639-020-10219-y

Almohammad, K., Hagras, H., Alghazzawi, D., & Aldabbagh, G. (2017). A survey of artificial intelligence techniques employed for adaptive edu- cational systems within e-learning platforms. *Journal of Artificial Intelli- gence and Soft Computing Research*, *7*(1), 47–64. https://doi.org/10. 1515/jaiscr-2017-0004

Alzahrani, A. S., Tsai, Y. S., Iqbal, S., Marcos, P. M. M., Scheffel, M., Drachsler, H., & Gasevic, D. (2023). Untangling connections between challenges in the adoption of learning analytics in higher education. *Education and Information Technologies*, *28*(4), 4563–4595. https://doi. org/10.1007/s10639-022-11323-xe

Apoki, U. C., Hussein, A. M. A., Al-Chalabi, H. K. M., Badica, C., & Mocanu, M. L. (2022). The role of pedagogical agents in personalised adaptive learning: A review. *Sustainability*, *14*(11), 6442. https://doi. org/10.3390/su14116442

Atalla, S., Daradkeh, M., Gawanmeh, A., Khalil, H., Mansoor, W., Miniaoui, S., & Himeur, Y. (2023). An intelligent recommendation sys- tem for automating academic advising based on curriculum analysis and performance modeling. *Mathematics*, *11*(5), 1098. https://doi.org/ 10.3390/math11051098

Aulakh, K., Roul, R. K., & Kaushal, M. (2023). E-learning enhancement through educational data mining with Covid-19 outbreak period in backdrop: A review. *International Journal of Educational Development*, *101*, 102814. https://doi.org/10.1016/j.ijedudev.2023.102814

Avram, M. R., & Pop, F. (2023). Real-time running workouts monitoring using cloud-edge computing. *Neural Computing and Applications*, *35*(19), 13803–13822. https://doi.org/10.1007/s00521-021-06675-3

Ayeni, O. O., Al Hamad, N. M., Chisom, O. N., Osawaru, B., & Adewusi, O. E. (2024). AI in education: A review of personalized learn- ing and educational technology. *GSC Advanced Research and Reviews*, *18*(2), 261–271. https://doi.org/10.30574/gscarr.2024.18.2.0062

Baig, M. I., & Yadegaridehkordi, E. (2024). Industry 5.0 applications for sus- tainability: A systematic review and future research directions. *Sustain- able Development*, *32*(1), 662–681. https://doi.org/10.1002/sd.2699

Baker, R. S., & Hawn, A. (2022). Algorithmic bias in education. *International Journal of Artificial Intelligence in Education*, *2022*(32), 1052–1092. https://doi.org/10.1007/s40593-021-00285-9

Barbieri, C. A., Rodrigues, J., Dyson, N., & Jordan, N. C. (2020). Improving fraction understanding in sixth graders with mathematics difficulties: Effects of a number line approach combined with cognitive learning strategies. *Journal of Educational Psychology*, *112*(3), 628. https://doi. org/10.1037/edu0000384

Barua, P. D., Vicnesh, J., Gururajan, R., Oh, S. L., Palmer, E., Azizan, M. M., & Acharya, U. R. (2022). Artificial intelligence enabled personalised assistive tools to enhance education of children with neu- rodevelopmental disorders—A review. *International Journal of Environ- mental Research and Public Health*, *19*(3), 1192. https://doi.org/10. 3390/ijerph19031192

Benvenuti, M., Cangelosi, A., Weinberger, A., Mazzoni, E., Benassi, M., Barbaresi, M., & Orsoni, M. (2023). Artificial intelligence and human behavioral development: A perspective on new skills and competences acquisition for the educational context. *Computers in Human Behavior*, *148*, 107903. https://doi.org/10.1016/j.chb.2023.107903

Berendt, B., Littlejohn, A., & Blakemore, M. (2020). AI in education: Learner choice and fundamental rights. *Learning, Media and Technology*, *45*(3), 312–324. https://doi.org/10.1080/17439884.2020.1786399

Borenstein, J., & Howard, A. (2021). Emerging challenges in AI and the need for AI ethics education. *AI and Ethics*, *1*, 61–65. https://doi.org/ 10.1007/s43681-020-00002-7

Caspari-Sadeghi, S. (2023). Learning assessment in the age of big data: Learning analytics in higher education. *Cogent Education*, *10*(1), 2162697. https://doi.org/10.1080/2331186X.2022.2162697

Cavanagh, T., Chen, B., Lahcen, R. A. M., & Paradiso, J. R. (2020). Con- structing a design framework and pedagogical approach for adaptive learning in higher education: A practitioner's perspective. *International Review of Research in Open and Distributed Learning 2020*, *21*(1), 173–197. https://doi.org/10.19173/irrodl.v21i1.4557

Celik, I., Dindar, M., Muukkonen, H., & Järvelä, S. (2022). The promises and challenges of artificial intelligence for teachers: A systematic review of research. *TechTrends*, *66*(4), 616–630. https://doi.org/10.1007/ s11528-022-00715-y

Chan, C. K. Y. (2023). A comprehensive AI policy education framework for university teaching and learning. *International Journal of Educational Technology in Higher Education*, *20*(1), 38. https://doi.org/10.1186/ s41239-023-00408-3

Chen, C. Y. (2022). Immersive virtual reality to train preservice teachers in managing students' challenging behaviours: A pilot study. *British Jour- nal of Educational Technology*, *53*(4), 998–1024. https://doi.org/10. 1111/bjet.13181

Chen, X., Zou, D., Xie, H., Cheng, G., & Liu, C. (2020). Two decades of arti- ficial intelligence in education. *Educational Technology & Society*, *25*(1), 28–47.

Cheng, L., Umapathy, K., Rehman, M., Ritzhaupt, A., Antonyan, K., Shidfar, P., & Abramowitz, B. (2023). Designing, developing, and vali- dating a measure of undergraduate students' conceptions of artificial intelligence in education. *Journal of Interactive Learning Research*, *34*(2), 275–311.

Cheung, S. K., Kwok, L. F., Phusavat, K., & Yang, H. H. (2021). Shaping the future learning environments with smart elements: Challenges and opportunities. *International Journal of Educational Technology in Higher Education*, *18*, 1–9. https://doi.org/10.1186/s41239-021-00254-1

Ciolacu, M., Tehrani, A. F., Binder, L., & Svasta, P. M. (2018). Education 4.0-artificial intelligence assisted higher education: Early recognition system with machine learning to support students' success. *IEEE 24th International Symposium for Design and Technology in Electronic Packag- ing (SIITME)*, 23–30. https://doi.org/10.1109/SIITME.2018.8599203

Contrino, M. F., Reyes-Millán, M., Vázquez-Villegas, P., & Membrillo-Hernández, J. (2024). Using an adaptive learning tool to improve student performance and satisfaction in online and face- to-face education for a more personalized approach. *Smart Learning Environments*, *11*(1), 6.

Crompton, H., & Burke, D. (2023). Artificial intelligence in higher educa- tion: The state of the field. *International Journal of Educational Technol- ogy in Higher Education*, *20*(1), 1–22. https://doi.org/10.1186/s41239- 023-00392-8

Currie, C., Rajanbabu, P., & King, D. (2022). A toolbox of adaptations for online delivery of SEL programming. *Journal of Online Learning Research*, *8*(1), 7–35.

de Vries, P. (2022). The ethical dimension of emerging Technologies in Engineering Education. *Education Sciences*, *12*(11), 754. https://doi. org/10.3390/educsci12110754

Delgado, H. O. K., de Azevedo Fay, A., Sebastiany, M. J., & Silva, A. D. C. (2020). Artificial intelligence adaptive learning tools: The teaching of English in focus. *BELT-Brazilian English Language Teaching Journal*, *11*(2), e38749. https://doi.org/10.15448/2178-3640.2020.2.38749

Demartini, C. G., Sciascia, L., Bosso, A., & Manuri, F. (2024). Artificial intelli- gence bringing improvements to adaptive learning in education: A case study. *Sustainability*, *16*(3), 1347. https://doi.org/10.3390/ su16031347

Deroncele-Acosta, A., Palacios-Núñez, M. L., & Toribio-López, A. (2023). Digital transformation and technological innovation on higher educa- tion post-COVID-19. *Sustainability*, *15*(3), 2466. https://doi.org/10. 3390/su15032466

Dhirani, L. L., Mukhtiar, N., Chowdhry, B. S., & Newe, T. (2023). Ethical dilemmas and privacy issues in emerging technologies: A review. *Sen- sors*, *23*(3), 1151. https://doi.org/10.3390/s23031151

Dogan, M. E., Goru Dogan, T., & Bozkurt, A. (2023). The use of artificial intelligence (AI) in online learning and distance education processes: A systematic review of empirical studies. *Applied Sciences*, *13*(5), 3056. https://doi.org/10.3390/app13053056

Dumont, H., & Ready, D. D. (2023). On the promise of personalized learn- ing for educational equity. *Npj Science of Learning*, *8*(1), 26. https://doi. org/10.1038/s41539-023-00174-x

Essa, S. G., Celik, T., & Human-Hendricks, N. E. (2023). Personalized adap- tive learning technologies based on machine learning techniques to identify learning styles: A systematic literature review. *IEEE Access*, *2023*(11), 48392–48409. https://doi.org/10.1109/ACCESS.2023. 3276439

Ferrara, E. (2023). Fairness and bias in artificial intelligence: A brief survey of sources, impacts, and mitigation strategies. *Sci*, *6*(1), 3. https://doi. org/10.3390/sci6010003

Ferri, F., Grifoni, P., & Guzzo, T. (2020). Online learning and emergency remote teaching: Opportunities and challenges in emergency situa- tions. *Societies*, *10*(4), 86. https://doi.org/10.3390/soc10040086

Flores-Vivar, J. M., & García-Peñalvo, F. J. (2023). Reflections on the ethics, potential, and challenges of artificial intelligence in the frame- work of quality education (SDG4). *Comunicar*, *31*(74), 37–47. https:// doi.org/10.3916/C74-2023-03

Foster, M. E. (2023). Evaluating the impact of supplemental computer- assisted math instruction in elementary school: A conceptual replica- tion. *Journal of Research on Educational Effectiveness*, *17*, 1–25. https:// doi.org/10.1080/19345747.2023.2174919

García-Martínez, I., Fernández-Batanero, J. M., Fernández-Cerero, J., & León, S. P. (2023). Analysing the impact of artificial intelligence and computational sciences on student performance: Systematic review and meta-analysis. *Journal of New Approaches in Educational Research*, *12*(1), 171–197. https://doi.org/10.7821/naer.2023.1.1240

Garrison, D. R. (2022). Shared metacognition in a community of inquiry. *Online Learning*, *26*(1), 6–18. https://doi.org/10.24059/olj.v26i1.3023

Garzón, J. (2021). An overview of twenty-five years of augmented reality in education. *Multimodal Technologies and Interaction*, *5*(7), 37. https://doi.org/10.3390/mti5070037

George, B., & Wooden, O. (2023). Managing the strategic transformation of higher education through artificial intelligence. *Administrative Sci- ences*, *13*(9), 196. https://doi.org/10.3390/admsci13090196

Gligorea, I., Cioca, M., Oancea, R., Gorski, A. T., Gorski, H., & Tudorache, P. (2023). Adaptive learning using artificial intelligence in e-learning: A lit- erature review. *Education Sciences*, *13*(12), 1216. https://doi.org/10. 3390/educsci13121216

Glover, T. A., Reddy, L. A., & Crouse, K. (2023). Instructional coaching actions that predict teacher classroom practices and student achieve- ment. *Journal of School Psychology*, *96*, 1–11. https://doi.org/10.1016/ j.jsp.2022.10.006

Google Trends. (2023). Improving Search Results. https://trends. google.com

Gorina, L., Gordova, M., Khristoforova, I., Sundeeva, L., & Strielkowski, W. (2023). Sustainable education and digitalization through the prism of the COVID-19 pandemic. *Sustainability*, *15*(8), 6846. https://doi.org/ 10.3390/su15086846

Grassini, S. (2023). Shaping the future of education: Exploring the potential and consequences of AI and ChatGPT in educational settings. *Educa- tion Sciences*, *13*(7), 692. https://doi.org/10.3390/educsci13070692

Guo, L., Wang, D., Gu, F., Li, Y., Wang, Y., & Zhou, R. (2021). Evolution and trends in intelligent tutoring systems research: A multidisciplinary and scientometric view. *Asia Pacific Education Review*, *22*(3), 441–461. https://doi.org/10.1007/s12564-021-09697-7

Hagadone-Bedir, M., Voithofer, R., & Kulp, J. T. (2023). Contextualizing privacy with wearable data in higher education. *British Journal of Edu- cational Technology*, *54*(6), 1619–1635. https://doi.org/10.1111/bjet. 13378

Hazra, A., Rana, P., Adhikari, M., & Amgoth, T. (2023). Fog computing for next-generation internet of things: Fundamental, state-of-the-art and research challenges. *Computer Science Review*, *48*, 100549. https://doi. org/10.1016/j.cosrev.2023.100549

He, D., Yao, Z., Tang, P., & Ma, Y. (2023). Impacts of different interactions on viewers' sense of virtual community: An empirical study of live streaming platform. *Behaviour & Information Technology*, *42*(7), 940– 960. https://doi.org/10.1080/0144929X.2022.2053884

Heim, A., Bharani, T., Konstantinides, N., Powell, J., Srivastava, S., Cao, X., Agarwal, D., Waiho, K., Lin, T., Virgüez, E., Strielkowski, W., & Uzonyi, A. (2023). AI in search of human help. *Science*, *381*(6654), 162–163. https://doi.org/10.1126/science.adi8740

Holman, D., & Švejdarová, E. (2023). The 21st-century empowering wholeness adaptive (EWA) educational model transforming learning capacity and Human capital through wholeness systems thinking towards a sus- tainable future. *Sustainability*, *15*(2), 1301. https://doi.org/10.3390/ su15021301

Holmes, W., Porayska-Pomsta, K., Holstein, K., Sutherland, E., Baker, T., Shum, S. B., & Koedinger, K. R. (2021). Ethics of AI in education: Towards a community-wide framework. *International Journal of Artifi- cial Intelligence in Education*, *32*, 1–23. https://doi.org/10.1007/ s40593-021-00239-1

Huynh-The, T., Pham, Q. V., Pham, X. Q., Nguyen, T. T., Han, Z., & Kim, D. S. (2022). Artificial intelligence for the metaverse: A survey. *arXiv Preprint arXiv*, *2202*, 10336. https://doi.org/10.1016/j.engappai. 2022.105581

Jaiswal, A., & Arun, C. J. (2021). Potential of artificial intelligence for trans- formation of the education system in India. *International Journal of Education and Development Using Information and Communication Tech- nology*, *17*(1), 142–158.

Jing, Y., Zhao, L., Zhu, K., Wang, H., Wang, C., & Xia, Q. (2023). Research landscape of adaptive learning in education: A bibliometric study on research publications from 2000 to 2022. *Sustainability*, *15*(4), 3115. https://doi.org/10.3390/su15043115

Jones, K. M. (2019). Learning analytics and higher education: A proposed model for establishing informed consent mechanisms to promote stu- dent privacy and autonomy. *International Journal of Educational Tech- nology in Higher Education*, *16*(1), 1–22. https://doi.org/10.1186/ s41239-019-0155-0

Kabudi, T., Pappas, I., & Olsen, D. H. (2021). AI-enabled adaptive learning systems: A systematic mapping of the literature. *Computers and Educa- tion: Artificial Intelligence*, *2*, 100017. https://doi.org/10.1016/j.caeai. 2021.100017

Kadaruddin, K. (2023). Empowering education through generative AI: Innovative instructional strategies for Tomorrow's learners. *Interna- tional Journal of Business, Law, and Education*, *4*(2), 618–625. https:// doi.org/10.56442/ijble.v4i2.215

Kamalov, F., Santandreu Calonge, D., & Gurrib, I. (2023). New era of artificial intelligence in education: Towards a sustainable multifaceted revolution. *Sustainability*, *15*(16), 12451. https://doi.org/10.3390/su151612451

Kant, N., Prasad, K. D., & Anjali, K. (2021). Selecting an appropriate learn- ing management system in open and distance learning: A strategic approach. *Asian Association of Open Universities Journal*, *16*(1), 79–97. https://doi.org/10.1108/AAOUJ-09-2020-007

Kasneci, E., Seßler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., & Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences*, *103*, 102274. https://doi.org/10.1016/j.lindif. 2023.102274

Kem, D. (2022). Personalised and adaptive learning: Emerging learning platforms in the era of digital and smart learning. *International Journal of Social Science and Human Research*, *5*(2), 385–391. https://doi.org/ 10.47191/ijsshr/v5-i2-02

Kesavan, N., Seenuvasaragavan, S., Burnette, K., Heim, A. B., Patel, R. J., Johnston, J., Cao, X., Sakandar, H. A., Zhuang, Y., Oi, K. K., Zhi, Y., Diao, Y., & Strielkowski, W. (2022). Pandemic-inspired policies. *Sci- ence*, *377*(6601), 22–24. https://doi.org/10.1126/science.add2046

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*, *1*, 1263555. https://doi.org/10.1155/2022/ 1263555

Khreisat, M. N., Khilani, D., Rusho, M. A., Karkkulainen, E. A., Tabuena, A. C., & Uberas, A. D. (2024). Ethical implications of ai inte- gration in educational decision making: Systematic review. *Educational Administration: Theory and Practice 2024*, *30*(5), 8521–8527. https:// doi.org/10.53555/kuey.v30i5.4406

Kooli, C. (2023). Chatbots in education and research: A critical examination of ethical implications and solutions. *Sustainability*, *15*(7), 5614. https://doi.org/10.3390/su15075614

Koutsantonis, D., Koutsantonis, K., Bakas, N. P., Plevris, V., Langousis, A., & Chatzichristofis, S. A. (2022). Bibliometric literature review of adaptive learning systems. *Sustainability*, *14*(19), 12684. https://doi.org/10.3390/su141912684

Kubsch, M., Krist, C., & Rosenberg, J. M. (2023). Distributing epistemic functions and tasks-a framework for augmenting human analytic power with machine learning in science education research. *Journal of Research in Science Teaching*, *60*(2), 423–447. https://doi.org/10. 1002/tea.21803

Lameras, P., & Arnab, S. (2021). Power to the teachers: An exploratory review on artificial intelligence in education. *Information*, *13*(1), 14. https://doi.org/10.3390/info13010014

Lee, S., & Lee, K. (2024). Smart teachers in smart schools in a smart city: Teachers as adaptive agents of educational technology reforms. *Learn- ing, Media and Technology*, *49*(3), 456–477. https://doi.org/10.1080/ 17439884.2023.2207143

Li, F., He, Y., & Xue, Q. (2021). Progress, challenges and countermeasures of adaptive learning. *Educational Technology & Society*, *24*(3), 238–255.

Li, X., Xu, H., Zhang, J., & Chang, H. H. (2023). Deep reinforcement learn- ing for adaptive learning systems. *Journal of Educational and Behavioral Statistics*, *48*(2), 220–243. https://doi.org/10.3102/107699862211 29847

Li, X.l., & Xia, J. (2020). School-based practice based on supplemental instruction of big data in education. *Science Insights Education Frontiers*, *7*(2), 913–933. https://doi.org/10.15354/sief.20.or063

Liu, M., Ren, Y., Nyagoga, L. M., Stonier, F., Wu, Z., & Yu, L. (2023). Future of education in the era of generative artificial intelligence: Consensus among Chinese scholars on applications of ChatGPT in schools. *Future in Educational Research*, *1*(1), 72–101. https://doi.org/10.1002/fer3.10

Liu, M., & Yu, D. (2023). Towards intelligent E-learning systems. *Education and Information Technologies*, *28*(7), 7845–7876. https://doi.org/10. 1007/s10639-022-11479-6

Luan, H., Geczy, P., Lai, H., Gobert, J., Yang, S. J., Ogata, H., & Tsai, C. C. (2020). Challenges and future directions of big data and artificial intel- ligence in education. *Frontiers in Psychology*, *11*, 580820. https://doi. org/10.3389/fpsyg.2020.580820

Lutz, C., & Newlands, G. (2021). Privacy and smart speakers: A multi- dimensional approach. *The Information Society*, *37*(3), 147–162. https://doi.org/10.1080/01972243.2021.1897914

Maghsudi, S., Lan, A., Xu, J., & van der Schaar, M. (2021). Personalized education in the artificial intelligence era: What to expect next. *IEEE Signal Processing Magazine*, *38*(3), 37–50. https://doi.org/10.1109/ MSP.2021.3055032

Magnisalis, I., Demetriadis, S., & Karakostas, A. (2011). Adaptive and intelli- gent systems for collaborative learning support: A review of the field. *IEEE Transactions on Learning Technologies*, *4*(1), 5–20. https://doi.org/ 10.1109/TLT.2011.2

Mahmood, M. R., Matin, M. A., Sarigiannidis, P., & Goudos, S. K. (2022). A comprehensive review on artificial intelligence/machine learning algo- rithms for empowering the future IoT toward 6G era. *IEEE Access*, *10*, 87535–87562. https://doi.org/10.1109/ACCESS.2022.3199689

Major, L., Francis, G. A., & Tsapali, M. (2021). The effectiveness of technology-supported personalised learning in low-and middle-income countries: A meta-analysis. *British Journal of Educational Technology*, *52*(5), 1935–1964. https://doi.org/10.1111/bjet.13116

Makurumidze, S., Sifile, O., Twesige, D., Gasheja, F., Gwangwava, E., Matowanyika, K., Chinofunga, S., Mbizo, R., & Sunday, K. (2024). Leveraging on the fourth industrial revolution by African accountants in the sustenance of SDGs and AU agenda 2063. *Sustainable Develop- ment*. https://doi.org/10.1002/sd.3110

Maphosa, V. (2021). Teachers' perspectives on remote-based teaching and learning in the COVID-19 era: Rethinking technology availability and suitability in Zimbabwe. *European Journal of Interactive Multimedia and Education*, *2*(1), e02105. https://doi.org/10.30935/ejimed/9684

Marjerison, R. K., & Gatto, A. (2024). Public sector digitalization, corrup- tion, and sustainability in the developing world: A scoping review. *Sus- tainable Development*. https://doi.org/10.1002/sd.2900

Markauskaite, L., Marrone, R., Poquet, O., Knight, S., Martinez- Maldonado, R., Howard, S., & Siemens, G. (2022). Rethinking the entwinement between artificial intelligence and human learning: What capabilities do learners need for a world with AI? *Computers and Edu- cation: Artificial Intelligence*, *2022*(3), 100056. https://doi.org/10. 1016/j.caeai.2022.100056

Marougkas, A., Troussas, C., Krouska, A., & Sgouropoulou, C. (2023). Vir- tual reality in education: A review of learning theories, approaches and methodologies for the last decade. *Electronics*, *12*(13), 2832. https:// doi.org/10.3390/electronics12132832

Marshall, R., Pardo, A., Smith, D., & Watson, T. (2022). Implementing next generation privacy and ethics research in education technology. *British Journal of Educational Technology*, *53*(4), 737–755. https://doi.org/10. 1111/bjet.13224

Martin, F., Chen, Y., Moore, R. L., & Westine, C. D. (2020). Systematic review of adaptive learning research designs, context, strategies, and technologies from 2009 to 2018. *Educational Technology Research and Development*, *68*, 1903–1929. https://doi.org/10.1007/s11423-020-09793-2

Matthew, U. O., Kazaure, J. S., & Okafor, N. U. (2021). Contemporary development in E-learning education, cloud computing technology & internet of things. *EAI Endorsed Transactions on Cloud Systems*, *7*(20), e3.

Maxfielf, C. (2023). Arizona State University to use adaptive learning tech- nology. *Eetimes* https://www.eetimes.com/arizona-state-university- to-use-adaptive-learning-technology

Meng, S. (2023). Enhancing teaching and learning: Aligning instructional practices with education quality standards. *Research and Advances in Education*, *2*(7), 17–31. https://doi.org/10.56397/RAE.2023.07.04

Mian, S. H., Salah, B., Ameen, W., Moiduddin, K., & Alkhalefah, H. (2020). Adapting universities for sustainability education in industry 4.0: Channel of challenges and opportunities. *Sustainability*, *12*(15), 6100. https://doi.org/10.3390/su12156100

Minn, S. (2020). AI-assisted knowledge assessment techniques for adap- tive learning environments. *Computers and Education: Artificial Intelli- gence*, *3*, 100050. https://doi.org/10.1016/j.caeai.2022.100050

Minyar-Beloroucheva, A., & Sergienko, P. (2022). Competences develop- ment within L2 PR undergraduates education in the digital age. *Amazo- nia Investiga*, *11*(50), 282–289. https://doi.org/10.34069/AI/2022.50. 02.26

Mirata, V., Hirt, F., Bergamin, P., & van der Westhuizen, C. (2020). Chal- lenges and contexts in establishing adaptive learning in higher educa- tion: Findings from a Delphi study. *International Journal of Educational Technology in Higher Education*, *2020*(17), 1–25. https://doi.org/10. 1186/s41239-020-00209-y

Mousavinasab, E., Zarifsanaiey, N. R., Niakan Kalhori, S., Rakhshan, M., Keikha, L., & Ghazi Saeedi, M. (2021). Intelligent tutoring systems: A systematic review of characteristics, applications, and evaluation methods. *Interactive Learning Environments*, *29*(1), 142–163. https:// doi.org/10.1080/10494820.2018.1558257

Muca, E., Buonaiuto, G., Lamanna, M., Silvestrelli, S., Ghiaccio, F., Federiconi, A., Matos, D., Vettori, J., Colleluori, R., Fusaro, I., Raspa, F., Valle, E., Formigoni, A., & Cavallini, D. (2023). Reaching a wider audi- ence: Instagram's role in dairy cow nutrition education and engage- ment. *Animals*, *13*(22), 3503. https://doi.org/10.3390/ani13223503

Muca, E., Cavallini, D., Raspa, F., Bordin, C., Bergero, D., & Valle, E. (2023). Integrating new learning methods into equine nutrition classrooms: The importance of students' perceptions. *Journal of Equine Veterinary Science*, *126*, 104537. https://doi.org/10.1016/j.jevs.2023.104537

Muñoz, J. L. R., Ojeda, F. M., Jurado, D. L. A., Peña, P. F. P., Carranza, C. P. M., Berríos, H. Q., & Vasquez-Pauca, M. J. (2022). Sys- tematic review of adaptive learning technology for learning in higher education. *Eurasian Journal of Educational Research*, *98*(98), 221–233.

Nguyen, A., Ngo, H. N., Hong, Y., Dang, B., & Nguyen, B. P. T. (2023). Ethi- cal principles for artificial intelligence in education. *Education and Infor- mation Technologies*, *28*(4), 4221–4241. https://doi.org/10.1007/ s10639-022-11316-w

Núñez-Canal, M., de Obesso, M. D. L. M., & Pérez-Rivero, C. A. (2022). New challenges in higher education: A study of the digital competence of educators in Covid times. *Technological Forecasting and Social Change*, *2022*(174), 121270. https://doi.org/10.1016/j.techfore.2021. 121270

Nureev, R., Volchik, V., & Strielkowski, W. (2020). Neoliberal reforms in higher education and the import of institutions. *Social Sciences*, *9*(5), 79. https://doi.org/10.3390/socsci9050079

Opesemowo, O. A. G., & Adekomaya, V. (2024). Harnessing artificial intelli- gence for advancing sustainable development goals in South Africa's higher education system: A qualitative study. *International Journal of Learning, Teaching and Educational Research*, *23*(3), 67–86. https://doi. org/10.26803/ijlter.23.3.4

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

Owan, V. J., Abang, K. B., Idika, D. O., Etta, E. O., & Bassey, B. A. (2023). Exploring the potential of artificial intelligence tools in educational measurement and assessment. *Eurasia Journal of Mathematics, Science and Technology Education*, *19*(8), em2307. https://doi.org/10.29333/ ejmste/13428

Purwanto, M. B., Hartono, R., & Wahyuni, S. (2023). Essential skills chal- lenges for the 21st century graduates: Creating a generation of high- level competence in The industrial revolution 4.0 era. *Asian Journal of Applied Education (AJAE)*, *2*(3), 279–292. https://doi.org/10.55927/ ajae.v2i3.3972

Putra, A., Gram, D., Stefanou, C., & Santoro, D. (2022). The use of adaptive learning technology to enhance learning in clinical veterinary derma- tology. *Journal of Veterinary Medical Education*, *49*(1), 118–125. https://doi.org/10.3138/jvme-2020-0069

Rahman, M. M., Shakeri, M., Tiong, S. K., Khatun, F., Amin, N., Pasupuleti, J., & Hasan, M. K. (2021). Prospective methodologies in hybrid renewable energy systems for energy prediction using artificial neural networks. *Sustainability*, *13*(4), 2393. https://doi.org/10.3390/ su13042393

Raj, N. S., & Renumol, V. G. (2022). A systematic literature review on adap- tive content recommenders in personalized learning environments from 2015 to 2020. *Journal of Computers in Education*, *9*(1), 113–148. https://doi.org/10.1007/s40692-021-00199-4

Rejmi, Z. H., & Rasli, R. M. (2022). MATHNECT: Mathematics motion based learning for primary school. *International Journal of Artificial Intelligence*, *9*(2), 49–62. https://doi.org/10.36079/lamintang.ijai-0902.456

Romanova, O. A., & Kuzmin, E. (2021). Industrial policy: A new reality in the context of digital transformation of the economy. *Lecture Notes in Information Systems and Organisation*, *44*, 13–23. https://doi.org/10. 1007/978-3-030-73261-5_2

Roshanaei, M., Olivares, H., & Lopez, R. R. (2023). Harnessing AI to Foster equity in education: Opportunities, challenges, and emerging strate- gies. *Journal of Intelligent Learning Systems and Applications*, *15*(4), 123–143. https://doi.org/10.4236/jilsa.2023.154009

Sá, M. J., & Serpa, S. (2020). The COVID-19 pandemic as an opportunity to foster the sustainable development of teaching in higher education. *Sustainability*, *12*(20), 8525. https://doi.org/10.3390/su12208525

Sahoo, S. (2022). Big data analytics in manufacturing: A bibliometric analy- sis of research in the field of business management. *International Jour- nal of Production Research*, *60*(22), 6793–6821. https://doi.org/10. 1080/00207543.2021.1919333

Sangiuliano Intra, F., Nasti, C., Massaro, R., Perretta, A. J., di Girolamo, A., Brighi, A., & Biroli, P. (2023). Flexible learning environments for a sustainable lifelong learning process for teachers in the school context. *Sustainability*, *15*(14), 11237. https://doi.org/10.3390/ su151411237

Scavarelli, A., Arya, A., & Teather, R. J. (2021). Virtual reality and aug- mented reality in social learning spaces: A literature review. *Virtual Reality*, *25*, 257–277. https://doi.org/10.1007/s10055-020-00444-8

Sharma, S. K., Woungang, I., Anpalagan, A., & Chatzinotas, S. (2020). Toward tactile internet in beyond 5G era: Recent advances, current issues, and future directions. *IEEE Access*, *8*, 56948–56991. https:// doi.org/10.1109/ACCESS.2020.2980369

Sharma, U., Tomar, P., Bhardwaj, H., & Sakalle, A. (2021). Artificial intelli- gence and its implications in education. In S. Verma & P. Tomar (Eds.), *Impact of AI technologies on teaching, learning, and research in higher education* (pp. 222–235). IGI Global Publishing. https://doi.org/10. 4018/978-1-7998-4763-2.ch014

Shemshack, A., Kinshuk, & Spector, J. M. (2021). A comprehensive analysis of personalized learning components. *Journal of Computers in Educa- tion*, *8*(4), 485–503. https://doi.org/10.1007/s40692-021-00188-7

Shemshack, A., & Spector, J. M. (2020). (2020). A systematic literature review of personalized learning terms. *Smart Learning Environments*, *7*(1), 33. https://doi.org/10.1186/s40561-020-00140-9

Simionescu, M., Strielkowski, W., & Gavurova, B. (2022). Could quality of governance influence pollution? Evidence from the revised environ- mental Kuznets curve in central and eastern European countries. *Energy Reports*, *8*, 809–819. https://doi.org/10.1016/j.egyr.2021. 12.031

Smith, J. (2022). Human-computer interaction: Enhancing user experience and productivity. *International Multidisciplinary Journal of Science, Tech- nology, and Business*, *1*(4), 1–4.

Smyrnova-Trybulska, E., Morze, N., & Varchenko-Trotsenko, L. (2022). Adaptive learning in university students' opinions: Cross-border research. *Education and Information Technologies*, *27*(5), 6787–6818. https://doi.org/10.1007/s10639-021-10830-7

Strielkowski, W., Samoilikova, A., Smutka, L., Civín, L., & Lieonov, S. (2022). Dominant trends in intersectoral research on funding innovation in business companies: A bibliometric analysis approach. *Journal of Inno- vation & Knowledge*, *7*(4), 100271. https://doi.org/10.1016/j.jik.2022. 100271

Tang, K. Y., Chang, C. Y., & Hwang, G. J. (2023). Trends in artificial intelligence-supported e-learning: A systematic review and co-citation network analysis (1998–2019). *Interactive Learning Environments*, *31*(4), 2134–2152. https://doi.org/10.1080/10494820.2021.1875001

Tao, X., Hanif, H., Ahmed, H. H., & Ebrahim, N. A. (2021). Bibliometric anal- ysis and visualization of academic procrastination. *Frontiers in Psychol- ogy*, *12*, 722332. https://doi.org/10.3389/fpsyg.2021.722332

Tapalova, O., & Zhiyenbayeva, N. (2022). Artificial intelligence in educa- tion: AIEd for personalised learning pathways. *Electronic Journal of e-Learning*, *20*(5), 639–653. https://doi.org/10.34190/ejel.20.5.2597

Troussas, C., Krouska, A., Kabassi, K., Sgouropoulou, C., & Cristea, A. I. (2022). Artificial intelligence techniques for personalized educational software. *Frontiers in Artificial Intelligence*, *5*, 988289. https://doi.org/ 10.3389/frai.2022.988289

Tsai, S. C., Chen, C. H., Shiao, Y. T., Ciou, J. S., & Wu, T. N. (2020). Preci- sion education with statistical learning and deep learning: A case study in Taiwan. *International Journal of Educational Technology in Higher Edu- cation*, *17*, 1–13. https://doi.org/10.1186/s41239-020-00186-2

Tzenios, N. (2020). Examining the impact of EdTech integration on aca- demic performance using random Forest regression. *ResearchBerg Review of Science and Technology*, *3*(1), 94–106.

Valdés, K. N., & Cerdá Suárez, L. M. (2021). An institutional perspective for evaluating digital transformation in higher education: Insights from the Chilean case. *Sustainability*, *13*(17), 9850. https://doi.org/10.3390/ su13179850

Vesin, B., Mangaroska, K., Akhuseyinoglu, K., & Giannakos, M. (2022). Adaptive assessment and content recommendation in online program- ming courses: On the use of Elo-rating. *ACM Transactions on Comput- ing Education (TOCE)*, *22*(3), 1–27. https://doi.org/10.1145/3511886

von Winckelmann, S. L. (2023). Predictive algorithms and racial bias: A qualitative descriptive study on the perceptions of algorithm accuracy in higher education. *Information and Learning Sciences*, *124*(9/10), 349–371. https://doi.org/10.1108/ILS-05-2023-0045

Walker, K. L., Bodendorf, K., Kiesler, T., de Mattos, G., Rostom, M., & Elkordy, A. (2023). Compulsory technology adoption and adaptation in education: A looming student privacy problem. *Journal of Consumer Affairs*, *57*(1), 445–478. https://doi.org/10.1111/joca.12506

Wang, S., Christensen, C., Cui, W., Tong, R., Yarnall, L., Shear, L., & Feng, M. (2023). When adaptive learning is effective learning: Com- parison of an adaptive learning system to teacher-led instruction.

Interactive Learning Environments, *31*(2), 793–803. https://doi.org/10.1080/10494820.2020.1808794

WestEd. (2017). Carnegie Math Pathways Graduates to Larger Home in WestEd. https://www.wested.org/wested-bulletin/news/carnegie- math-pathways-graduates-to-larger-home-in-wested

Whalley, B., France, D., Park, J., Mauchline, A., & Welsh, K. (2021). Towards flexible personalized learning and the future educational sys- tem in the fourth industrial revolution in the wake of Covid-19. *Higher Education Pedagogies*, *6*(1), 79–99. https://doi.org/10.1080/23752696.2021.1883458

Wiggins, W. F., Caton, M. T., Magudia, K., Glomski, S. H. A., George, E., Rosenthal, M. H., & Andriole, K. P. (2020). Preparing radiologists to lead in the era of artificial intelligence: Designing and implementing a focused data science pathway for senior radiology residents. *Radiology: Artificial Intelligence*, *2*(6), e200057. https://doi.org/10.1148/ryai.2020200057

Wolff, M., Hammoud, M., & Carney, M. (2023). Developing master adaptive learners: Implementation of a coaching program in graduate medi- cal education. *Western Journal of Emergency Medicine*, *24*(1), 71. https://doi.org/10.5811/westjem.2022.12.57636

Wongvorachan, T., Lai, K. W., Bulut, O., Tsai, Y. S., & Chen, G. (2022). Artificial intelligence: Transforming the future of feedback in education. *Journal of Applied Testing Technology*, *23*, 95–116.

Worth, E., Reeves, A., & Friedman, S. (2023). Is there an old girls' network? Girls' schools and recruitment to the British elite. *British Journal of Sociology of Education*, *44*(1), 1–25. https://doi.org/10.1080/01425692.2022.2132472

Xie, H., Chu, H. C., Hwang, G. J., & Wang, C. C. (2019). Trends and development in technology-enhanced adaptive/personalized learning: A systematic review of journal publications from 2007 to 2017. *Computers & Education*, *140*, 103599. https://doi.org/10.1016/j.compedu.2019.103599

Yang, A. C., Flanagan, B., & Ogata, H. (2022). Adaptive formative assessment system based on computerized adaptive testing and the learning memory cycle for personalized learning. *Computers and Education: Artificial Intelligence*, *2022*(3), 100104. https://doi.org/10.1016/j.caeai.2022.100104

Yuan, X., Yu, L., & Wu, H. (2021). Awareness of sustainable development goals among students from a Chinese senior high school. *Education Sciences*, *11*(9), 458. https://doi.org/10.3390/educsci11090458

Yun, C., Shun, M., Junta, U., & Browndi, I. (2022). Predictive analytics: A survey, trends, applications, Opportunities' and challenges for Smart City planning. *International Journal of Computer Science and Information Technology*, *23*(56), 226–231.

Zainuddin, Z., Shujahat, M., Haruna, H., & Chu, S. K. W. (2020). The role of gamified e-quizzes on student learning and engagement: An interac- tive gamification solution for a formative assessment system. *Com- puters & Education*, *145*, 103729. https://doi.org/10.1016/j.compedu.2019.103729

Zarifian, M., Volkova, I., & Lazutova, N. (2022). The evolution of cartoons throughout the history of mass communication. *International Journal of Media and Information Literacy*, *7*(2), 629–638. https://doi.org/10.13187/ijmil.2022.2.629

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education–where are the educators? *International Journal of Educational Technology in Higher Education*, *16*(1), 1–27. https://doi.org/10.1186/s41239-019-0171-0

Zhai, C., Wibowo, S., & Li, L. D. (2024). The effects of over-reliance on AI dialogue systems on students' cognitive abilities: A systematic review. *Smart Learning Environments*, *11*(1), 28. https://doi.org/10.1186/s40561-024-00316-7

Zhai, X., Chu, X., Chai, C. S., Jong, M. S. Y., Istenic, A., Spector, M., & Li, Y. (2021). A review of artificial intelligence (AI) in education from 2010 to 2020. *Complexity*, *2021*(1), 8812542. https://doi.org/10.1155/2021/8812542

Zhai, X., Chu, X., Chai, C. S., Jong, M. S. Y., Istenic, A., Spector, M., & Li, Y. A. (2021) Review of artificial intelligence (AI) in education from 2010 to 2020. *Complexity*, *2021*, 1–18. https://doi.org/10.1155/2021/8812542

Zhong, S., Zhang, K., Bagheri, M., Burken, J. G., Gu, A., Li, B., & Zhang, H. (2021). Machine learning: New ideas and tools in environmental science and engineering. *Environmental Science & Technology*, *55*(19), 12741–12754. https://doi.org/10.1021/acs.est.1c01339

Zhukova, O., Platash, L., & Tymchuk, L. (2022). Inclusive education as a tool for implementing the sustainable development goals on the basis of humanization of society. *Problemy Ekorozwoju*, *17*(1), 114–122. https://doi.org/10.35784/pe.2022.1.11