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Review Article

Personalized learning through AI: Pedagogical approaches and critical insights

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ABSTRACT

In this analysis, we review artificial intelligence (AI)-supported personalized learning (PL) systems, with an emphasis on pedagogical approaches and implementation challenges. We searched the Web of Science and Scopus databases. After the preliminary review, we examined 30 publications in detail. ChatGPT and machine learning technologies are among the most often utilized tools; studies show that general education and language learning account for the majority of AI applications in the field of education. Supported by particular learning approaches stressing student characteristics and expectations, the results show that automated feedback systems and adaptive content distribution define AI's educational responsibilities mostly. The study notes major difficulties in three areas: technical constraints and data privacy concerns; educational and pragmatic barriers. Although curriculum integration and teacher preparation are considered major concerns, pedagogical challenges come first above technology integration. The results also underline the need for thorough professional development activities for teachers and AI tools for especially targeted instruction. The study shows that the efficient application of AI-enabled PL requires a comprehensive strategy addressing technological, pedagogical, and ethical issues all at once. These results help to describe the current state of AI in education and provide ideas for future developments as well as techniques for its use.

Keywords: artificial intelligence, personalized learning, adaptive learning, intelligent tutoring systems, ethics in AI education

INTRODUCTION

New advances in educational technologies present fresh opportunities for classroom and learning environment customizing. Particularly with the advancement of artificial intelligence (AI) technology, AI tools assist in building learning environments that can be customized to the needs, learning styles, and preferences of every student (Abbas et al., 2023; Akgun & Greenhow, 2022). Away from the conventional "one-size-fits-all" educational model, the tailored learning method offers a vision of education in which every student may advance at their own pace and in their own style.

AI systems provide real-time feedback, dynamically changing learning materials, and individualized learning paths by assessing student learning processes (Li & Wong, 2023; Tonbuloğlu, 2023). Apps such as intelligent tutoring systems (ITS) and chatbots help students boost their problem-solving skills and self-efficacy by providing instant support (Bahroun et al., 2023; Wu & Yu, 2024).

Examining the literature reveals, meanwhile, that pedagogical aspects in AI-supported tailored learning systems are not given enough attention. Particularly, thorough investigation on the pedagogical strategies applied in the integration of these technologies into educational processes, the difficulties and constraints faced is much needed (Mahmudi et al., 2023; Namaziandost & Rezai, 2024). In addition, issues such as ethical concerns, data privacy, and security regarding the use of AI technologies in education stand out as areas that need to be examined in depth.

The aim of this study is to reveal the current trends, pedagogical approaches and challenges encountered in the implementation process in the field of AI-supported personalized learning (PL) through a systematic literature review. In line with this purpose, the following research questions were sought to be answered:

1. What are the methodological characteristics (research area, method, and sample) of AI-supported PL studies?
2. What are the roles of AI in PL settings?
3. What are the pedagogical approaches used in AI-supported PL settings?
4. What are the challenges and limitations encountered in AI PL applications?

The existing state of the art in the field of AI-supported PL is expected to be fully presented in this work, which also offers direction for further studies and implementation. More specifically, it aims to provide teachers and scholars feasible recommendations on how to use AI technologies in the classroom. It is also intended to point out areas of research lacking in this subject and offer fresh directions for next projects. By offering a whole view of AI-supported PL, which is becoming more and more vital in the field of educational technologies, the study is expected to add to both theoretical knowledge and practical implementations.

LITERATURE REVIEW

Artificial Intelligence in Education

AI is the definition of computer systems solving difficult problems and emulating human intellect. Supported by sophisticated technologies such as machine learning (ML) and deep learning, AI presents revolutionary improvements in many sectors from education to health, from manufacturing to the service sector (Akgun & Greenhow, 2022; Russell & Norvig, 2016). Its possibilities in education are obviously evident from its several applications, which range from personalizing learning processes, measuring student progress, and providing effective feedback systems to these studies underline the moral and social issues related to the use of these technologies even while they indicate how competent AI is to transform education (Li & Wong, 2023).

AI integration in educational environments is becoming more and more common since it offers several possibilities in several learning situations. Including AI in learning environments calls for a whole approach, including technological, pedagogical, and cultural aspects. The uses of AI in education are investigated in this synthesis together with its benefits, drawbacks, and changing focus in study. Culture is therefore highly crucial since it shapes the acceptability and implementation of AI in the educational domain. Ma et al. (2024) conducted a comparison study based on their opinions and behavioral intentions to indicate foreign students have a greater attraction toward AI than their Chinese counterparts. This underlines the need to consider several cultural points of view and create individual strategies to effectively apply AI in higher education.

Integrating AI into education through tutoring and adaptive learning delivers data-driven insights that meet specific learner needs. AI algorithms are able to analyze large amounts of student data to predict student performance and tailor educational content, accordingly, thus providing a more customized learning experience than the traditional "one-size-fits-all" approach (Abbas et al., 2023; Tonbuloğlu, 2023). Such personalizing helps to create a learning atmosphere that raises student enthusiasm and involvement (Roshanaei et al., 2023). Mobile learning powered by AI (mLearning) is transforming digital education in line with pedagogical ideas. Based on a review of the literature, a framework emphasizes the need for including AI in mLearning environments to improve learning outcomes while handling issues including the misuse of cellphones (Moya & Camacho, 2024).

AI also enables the development of ITS and chatbots that provide instant support to students. These tools increase students' problem-solving skills and self-efficacy by providing timely feedback and support (Bahroun et al., 2023; Wu & Yu, 2024). Moreover, the contributions of AI to education go beyond mere personalization and meeting individual needs, promoting student engagement and deep learning through interactive environments such as simulations and virtual reality (Katsamakas et al., 2024; Namaziandost & Rezai, 2024).

Although there are some possible benefits–including the incorporation of AI into education–there are certain challenges as well. One should consider the ethical, legal, and social dimensions of using AI for education. Of major importance are the protection of anonymity and the promotion of critical thinking as well as the quality, validity, and fair usage of AI (Namaziandost & Rezai, 2024). AI should be developed according to researchers to be inclusive and easily accessible for every student (Mahmudi et al., 2023; Roshanaei et al., 2023; Zawacki-Richter et al., 2019). Moreover, the essential in terms of preventing social marginalization is narrowing the digital divide and providing equal access to AI technologies.

The integration of AI into education also requires educators to be ready to use these technologies effectively. Many educators express their lack of knowledge about AI and its applications, which can be a barrier to the successful implementation of AI tools in the classroom (Kwak et al., 2022). Therefore, professional development and training programs are regarded as crucial to provide teachers with the required information and abilities for the appropriate use of AI in teaching processes (Abulibdeh et al., 2024; Al-Zyoud, 2020; Fissore et al., 2024).

Although AI has major chances to enhance teaching methods, a careful approach to this integration is quite important, and juggling ethical and cultural sensitivity with technological developments, one might maximize the advantages of AI and so reduce.

Personalized Learning

PL is a method of instruction catered to every student's unique learning rate, style, needs, and inclination. This strategy is to enable people to participate more actively and customistically in the learning process while making experience more efficient. Although this concept is not new in origin, its application area has expanded, especially with technological advances, and the effectiveness of this approach has greatly increased (Shemshack & Spector, 2020). PL, according to constructivist learning theory, supports the perspective that learning happens through social interactions and personal experiences (Xie et al., 2019).

PL is generally acknowledged as an instructional model in which the learning pace and teaching approach are optimized depending on the needs of every student (Bernacki et al., 2021), even if different use cases have defined it differently (Castro et al., 2024; Guettala et al., 2024; Walkington & Bernacki, 2020).This method lets instructional tactics, content, and learning goals vary depending on the particular needs of the student (Klašnja-Milićević et al., 2011).This feature of individualized learning creates a different learning process from the traditional uniform approach of education. While conventional learning models often offer all students the same pace and knowledge, PL offers a more flexible and efficient learning environment by customizing to the individual qualities of every learner. This variation raises students' inspiration so they may participate more actively in the course of learning and advance at their own speed.

This aspect of customized learning generates a unique learning process different from the conventional homogeneous framework of instruction. When the literature (Bernacki et al., 2021; Shemshack et al., 2021; Tetzlaff et al., 2021) is examined, it is seen that PL has various components:

1. **Student profile:** It is necessary to identify the individual characteristics, preferences, and learning styles of each student. The learner profile provides a basic source of data for tailoring the learning process.
2. **Content adaptation:** Adaptation of the instructional content in accordance with the student profile is one of the basic requirements of PL. This adaptation involves providing material customized to the learner's level of knowledge and learning style.
3. **Learning path:** The most suitable learning path in line with the demands of the learner is defined by their own will.
4. **Assessment:** Evaluation of the student's development by means of feedback systems and ongoing observation guarantees efficient control of the learning process.
5. **Technology support:** Implementation of PL depends much on digital platforms and adaptive learning systems.

Important components increasing the effectiveness of customized learning are big data analytics, AI, and ML. These technologies support adaptive learning approaches depending on the demands of the students by customizing the learning environment (Soler Costa et al., 2021). Technological advancements in this sense include relatively important adaptive learning systems, ITS, learning analytics and content creation made possible by AI. These systems simplify and enhance the learning process by virtue of their study of student behavior and provision of pertinent content and feedback (Khor & K, 2024; Yang & Ogata, 2023). The following part will go into great length on how AI supports the customized learning process.

There are some challenges and limitations in implementing PL models. These include data privacy and security, technological infrastructure requirements, teacher training, scaling challenges, and cost factors. Protection of personal data depends critically on data privacy and security (Maier & Klotz, 2022). The viability of these systems depends on safe storage and avoidance of data usage by students. The hardware and software needed for the operation of customized learning systems constitute part of the technological infrastructure needs (Abulibdeh et al., 2024). The inadequacy of these infrastructures, especially in developing countries, causes the implementation to remain limited. Similarly, teachers need to receive appropriate training to use these technologies effectively (Bingham et al., 2018). Scaling challenges and cost factors are other important barriers. It is imperative to develop models suitable for different student profiles and educational settings, but this scaling process is highly complex (Tetzlaff et al., 2021). Moreover, cost is a major constraint, especially in low- and middle-income countries (Alamri et al., 2020).

In modern education, PL pedagogical methods employ technology to customize students' learning experiences to their particular needs, preferences, and ability–is a rising essential tool. The results of research evaluating the fundamental ideas and approaches of tailored learning as well as technology advancements in this field are synthesized in this literature review. Integration of adaptive learning technologies that allow the modification of learning content and pace to fit individual student traits is one of the most basic elements of PL (Peng et al., 2019; Tang et al., 2019).

According to the literature, individualized learning advances learner autonomy and motivation in addition to material delivery (Cheng & Wang, 2021). PL models provide a number of difficulties, too, including data protection, technology infrastructure, and teacher training (Bingham et al., 2018; Fadieieva, 2023). Realizing the possible advantages of tailored learning technologies depends on addressing these difficulties.

Artificial Intelligence in Personalized Learning

AI has emerged as a transformative force in PL processes and customizes educational experiences by creating learning environments that are adaptive to student needs (Bhutoria, 2022; Kabudi et al., 2021). The integration of various AI technologies such as ML, natural language processing (NLP), and ITS into educational frameworks makes it possible to personalize learning experiences to match student preferences, performance levels, and learning styles (El-Sabagh, 2021; Sajja et al., 2024). This personalization provides a more effective and motivating learning process that focuses on individual student needs, far beyond the traditional "one-size-fits-all" approach (Alamri et al., 2020; Bayly-Castaneda et al., 2024).

AI technologies are increasingly being used in the development of adaptive learning platforms that adjust learning content and teaching methods according to individual student profiles. These platforms improve student engagement and learning outcomes by providing personalized feedback and recommendations (Kochmar et al., 2022; Sayed et al., 2023). ITS and multi-agent systems develop student-specific learning pathways using educational data mining to build detailed student profiles and provide personalized educational content (Lippert et al., 2020). Developed specifically for specific subjects such as programming, AI-powered platforms dynamically adapt to users' skill levels and learning goals, providing personalized video recommendations and performance assessments (Pesovski et al., 2024). These adaptive systems not only enable learners to receive content in accordance with their individual needs and pace but also increase motivation and learning effectiveness.

Driven by AI, PL systems maximize training in line with student needs, therefore increasing educational efficiency. This raises student participation and educational fairness (Katiyar et al., 2024). Thanks to adaptive material distribution, students study at their own speed and in line with their own strengths and deficiencies, generating deeper information and more important learning opportunities (Al-Badi et al., 2022; Alenezi, 2023). Furthermore, AI technologies facilitate continuous learning through customized learning pathways that align with the changing requirements of learners across various contexts, such as career advancement and higher education, thus providing support. For example, Khan Academy's AI-driven tutor Khanmigo (Yan et al., 2024) provides educators with tailored activities and quick feedback, thereby enhancing learning outcomes; it also supports data analysis and lesson planning.

Despite its benefits, integrating AI into PL comes with a number of challenges, such as costs, infrastructure requirements, and privacy issues (Xie, 2024; Yılmaz, 2024). For AI technologies to be successfully implemented in classroom environments, teacher preparation is crucial. Teachers should graduate from this curriculum with skills in data analysis, pedagogical integration, and AI tool use. For instance, some projects have proven positive results by providing teachers with practical training on classroom uses of AI-supported platforms (Bondie, 2023; Seo et al., 2024). Furthermore, ethical questions like possible biases in AI algorithms should be answered to ensure fair and responsible implementation of AI technologies (Köbis & Mehner, 2021; Tsamados et al., 2022).

The future of AI in PL is moving towards offering increasingly advanced personalization capabilities through adaptive learning systems, virtual tutors, and immersive learning environments (Usak, 2024; Yılmaz, 2024). PL experiences are drawing more and more attention as they are taken farther using techniques like big language models–especially ChatGPT (Bayly-Castaneda et al., 2024). If we are to make use of AI in the classroom, research and development projects have to be kept in motion. Thus, this approach has to keep important human elements such as empathy and contextual awareness (Katiyar et al., 2024; Oberdieck & Moch, 2024).

The use of AI has a significant ability to transform customized learning environments by providing flexible, interactive, data-driven learning opportunities. The ability to provide customized materials depending on the needs of the student marks one major departure from accepted knowledge in education. Though, realizing the full promise of AI in tailored learning hinges on addressing concerns including ethics, privacy, infrastructure, and teacher development. By means of a harmonic mix of AI and human education, one guarantees that empathy and contextual understanding remain essential for the learning process, therefore improving the efficacy of education. Scientific and technological developments should be embraced by educational institutions since they greatly enhance the results of their operations. Nevertheless, challenges may arise in implementing these concepts, including insufficient funding, resistance to change, and inadequate infrastructure. Employing these tools will facilitate the development of effective, engaging, and adaptable learning environments.

METHODOLOGY

This study adopted a structured systematic literature review methodology. A systematic literature review offers a systematic and transparent approach to comprehensively identify, evaluate, and synthesize the

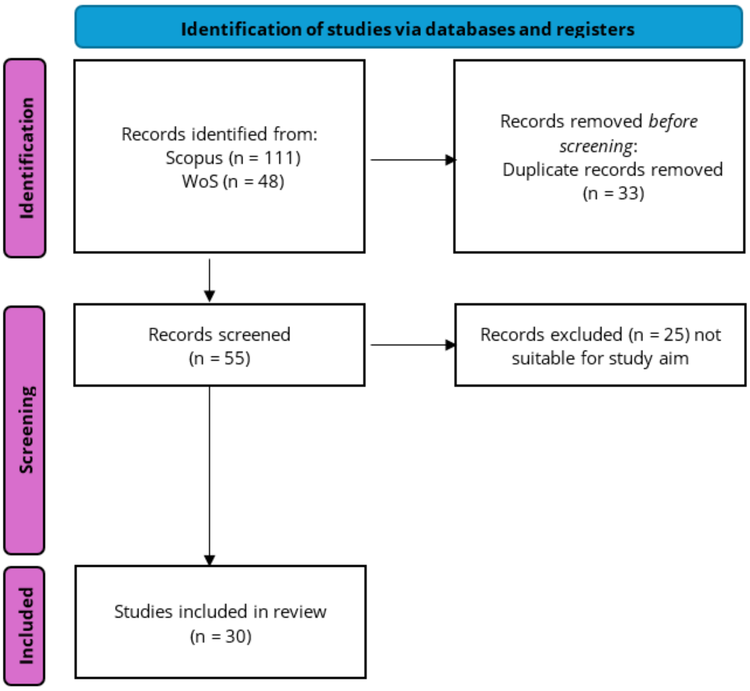

Figure 1. Flow chart based on PRISMA (the authors' own work)

existing literature on a specific research question (Xiao & Watson, 2019). This methodological approach allows identifying current research trends and gaps, especially in rapidly developing fields such as education (Newman & Gough, 2020). The PRISMA standards were followed throughout the investigation (Page et al., 2021). Using this technique ensures that the literature review process is rigorous and reproducible. The project was established to investigate the many educational tactics that could be used at the junction of AI and PL.

Data Collection Process

In this study, the data collection process was carried out with a systematic approach (as shown in **Figure 1**). The following search index was used to search the databases:

Search query: ((“personalized learning” OR “individualized learning” OR “adaptive learning”) AND (“artificial intelligence” OR “AI” OR “machine learning”) AND (“pedagog*” OR “teaching approach*” OR “educational method*”))

Inclusion criteria

1. Published between 2010 and 2024
2. Written in English
3. Research articles published in refereed journals
4. It has addressed both AI and PL issues together
5. Having full text access

Exclusion criteria

1. Published before 2010
2. Written in languages other than English
3. Types of publications other than research articles such as reviews, book chapters, and conference proceedings
4. Studies that focus only on AI or only on PL
5. Studies without full-text access

In line with the criteria determined, the data collection process was carried out in two stages. In the first search, 111 articles were obtained from the Scopus database and 48 articles from the Web ofScience (WoS) database. Since 33 of the articles obtained from WoS were also included in Scopus, duplicate records were removed.

In the first stage, the titles and abstracts of the articles were reviewed by two independent researchers, and 55 articles were identified in line with the inclusion criteria. In the second stage, the full texts of the selected articles were examined in detail, and 30 articles that were suitable for the purpose of the study were included in the final analysis. This systematic data collection process was documented in detail to increase the reliability and replicability of the research. Selection criteria and elimination processes were transparently reported.

Data Analysis

The data acquired from the systematic literature review was subjected in this study to a qualitative content analysis method. Considered a useful technique for methodically classifying textual material and arranging them into relevant themes is qualitative content analysis (Krippendorff, 2018). Particularly in light of this study, this strategy helped to enable a thorough analysis of the data and a deeper knowledge of the impact of AI on tailored learning. These phases are complementary to one another, and the study method seeks to assess the data holistically. There were three primary phases to this study's analytical process:

1. **Descriptive interpretation:** Descriptive statistics was used in the first stage to examine the methodological traits (research area, technique, sample) of the chosen papers. This study seeks to expose the general patterns and methodological strategies of works in literature.
2. **Thematic study:** In the second stage, using thematic analysis, the function of AI in PL processes, technologies applied, and pedagogical strategies underlined in detail. The six-stage analytical framework suggested by Braun and Clarke (2006) was chosen in thematic analysis since it leaves a methodical and thorough review of the data:
    a. Familiarization with data
    b. Generation of startup codes
    c. Searching for themes
    d. Review of themes
    e. Identification and naming of themes
    f. Preparation of the report

    This systematic process enabled the identification of meaningful and recurrent themes related to the research questions.
3. **Analysis of challenges and limitations:** In the third stage, the challenges and limitations encountered during the implementation process were analyzed. In this analysis, the main themes such as lack of resources, user resistance and technological infrastructure deficiencies were emphasized and case studies related to these situations were evaluated. In this analysis, the matrix approach proposed by Miles et al. (2014) was used. This method allowed for a systematic comparison and categorization of the challenges identified in different studies. Thus, it was possible to evaluate common problems encountered in practice from a holistic perspective.

Validity and Reliability

Various strategies were applied to ensure the validity and reliability of the study. In order to increase coding reliability, two researchers independently coded the data and inter-coder reliability was calculated using Miles and Huberman (1994) formula: Reliability = Agreement/(Agreement + disagreement)

The consensus rate, which was calculated as 82% in the first coding, increased to 100% as a result of the researchers' discussions and reorganization of the codes.

In order to increase internal validity, the themes and categories obtained were supported with direct quotations, thus ensuring a better understanding of the findings in context (Creswell & Clark, 2017). In order to ensure external validity, the research process, coding scheme and analysis steps were reported in detail.

Table 1. Descriptive statistics for studies

ID	Author(s)	Field	Type	Sample
S01	Albdrani and Al-Shargabi (n. d.)	Data science	Mixed-methods	20 university students
S02	Ariely et al. (2024)	Science education	Mixed-methods	607 high school students
S03	Baltezarević and Baltezarević (2024)	General education	Quantitative	219 university students
S04	Copur-Gencturk et al. (2024)	Professional development	Mixed-methods	52 teachers
S05	Duran (2024)	General education	Qualitative	118 teacher candidates
S06	Guo and Li (2024)	Language education	Mixed-methods	69 undergraduate students
S07	Hang et al. (2024)	General education	Mixed-methods	605 MCQs & 3 evaluators
S08	Harati et al. (2021)	Math & science	Mixed-methods	120 chemistry students
S09	Kaiss et al. (2023)	Programming	Mixed-methods	71 engineering students
S10	Kaouni et al. (2023)	General education	Design-based	Not specified
S11	Kucirkova and Leaton Gray (2023)	Democratic education	Theoretical	Not specified
S12	Li and Kim (2024)	Language education	Mixed-methods	93 students total
S13	Lan and Chen (2024)	Science education	Qualitative	Not specified
S14	Lee and Yeo (2022)	Mathematics education	Design-based	23 PSTs
S15	Lippert et al. (2020)	General education	Mixed-methods	Multiple groups
S16	Liu (2024)	Language education	Mixed-methods	Unspecified
S17	Mondal et al. (2023)	Medical sducation	Qualitative	Not specified
S18	Naz and Robertson (2024)	Language education	Mixed-methods	4 writing samples
S19	Ocumpaugh et al. (2024)	General education	Theoretical	Not specified
S20	Radif and Hameed (2024)	General education	Quantitative	College students
S21	Sachete et al. (2024)	General education	Mixed-methods	30 teachers
S22	Shankar et al. (2024)	STEM	Qualitative	67 STEM teachers
S23	Slamet (2024)	Language education	Quantitative	126 participants
S24	Tapalova and Zhiyenbayeva (2022)	General education	Mixed-methods	184 university students
S25	Ulla et al. (2024)	Language education	Qualitative	14 English teachers
S26	Villegas-Ch et al. (2024)	General education	Mixed-methods	450 university students
S27	Xiao and Zhi (2023)	Language education	Qualitative	5 undergraduate students
S28	Li (2024)	Language education	Mixed-methods	100 students
S29	Yeh (2024)	Language education	Qualitative	13 teachers
S30	Zhou (2023)	General education	Quantitative	356 university students

Following the qualitative content analysis criteria proposed by Forman and Damschroder (2007) helped to raise the methodological quality of the research. Particularly in the coding process, these standards help to guarantee the systematicity and dependability of the research by means of which consistency is raised. For the coding scheme, for instance, it was imperative to define each code precisely and verify uniformity among programmers. These standards included developing a methodical coding system, verifying coding scheme consistency, and honestly reporting results.

FINDINGS

Descriptive Information

When the descriptive statistics are analyzed, important patterns emerge (**Table 1**). When we look at the field distribution of the reviewed studies, general education (11 studies) and language education (9 studies) stand out as the most preferred fields by researchers. Although there are also studies in specialized fields such as STEM, data science and medical education, the number of studies in these fields is more limited. This shows that AI-supported PL research is concentrated in general education and language teaching.

When methodological preferences are examined, it is seen that mixed-methods approach is the dominant research design with 15 studies. This is followed by qualitative research with 7 studies and quantitative research with 4 studies. Theoretical and design-based research are less preferred approaches with 2 studies each. The prevalence of mixed method approach shows that PL is considered as a multidimensional phenomenon that needs to be supported by both quantitative and qualitative data.

In terms of sample characteristics, a specific sample group was defined in 25 of the 30 studies. Sample sizes ranged widely from 5 to 607. Although both students and teachers were selected as the target group in the studies, it is noteworthy that university students were the most common sample group. This reflects a growing interest in PL practices in higher education.

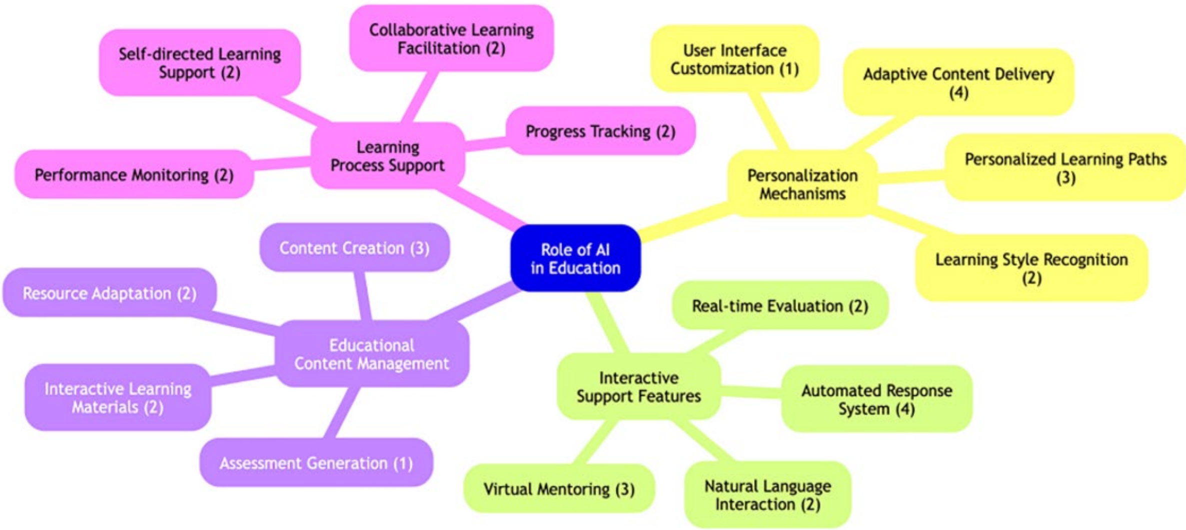

Figure 2. Concept map about role of AI in personalized learning (the authors' own work)

Role of Artificial Intelligence

The concept map "role of artificial intelligence in education" indicates how AI fulfills its functions within the educational context across four primary domains (as shown in **Figure 2**). The most often occurring codes are "automated response system" and "adaptive content delivery," each with a frequency of 4. This suggests that the utilization of AI as a content adaptation and automated feedback system is of the utmost relevance. This underlines in teaching the need to personalize and getting quick comments. Among the codes of medium frequency, "personalized learning paths," "virtual mentoring," and "content creation" (each f = 3) show that the function of AI in customizing the learning process and content development is also crucial. The fact that the codes with the lowest frequency are "user interface customization" and "assessment generation" (f = 1 each) suggests that the use of AI in these areas has not yet become widespread enough or has not been sufficiently addressed in research.

In terms of categories, the fact that "personalization mechanisms" and "interactive support features" categories contain higher frequency codes indicates that AI is used intensively in education, especially in the areas of personalization and interactive support. The fact that all codes in the "learning process support" category have equal frequency (f = 2) reveals that the roles of supporting the learning process show a balanced distribution. In the "educational content management" category, the fact that the frequencies vary (f = 1 to f = 3) shows that the use of AI in content management has different focal points.

Used Artificial Intelligence Technologies and Tools

Studies on the use of AI technologies and tools in the context of PL expose notable variations depending on the kinds, frequency of use and variety of these tools (as shown in **Figure 3**). With 11 studies overall, ChatGPT with all its iterations is the most often utilized AI tool. Following ChatGPT, ML and NLP technologies are the second most frequently used tools with 4 studies each. Tools such as Knowji and Gradescope were used in two studies each, and similarly neural networks were used in two studies. AI tools including Watson Assistant, Duolingo, and ALEKS are used in one study.

Having 11 AI technologies total, "core AI technologies" is the most regularly used category when AI tools are rated in terms of usage. The 13 applications of the "generative AI (GenAI)" category follow it. Though each of them was utilized in only one study, instruments designed especially for language acquisition vary in four different forms. Knowji has been applied twice in the field of learning management since there are four tools there. According to the research, GenAI tools–especially ChatGPT–play a major part in educational environments. Basic AI technologies such as ML and NLP are also widely adopted. The fact that most of these tools have only been used once suggests that research in this area is largely experimental. The variety of specialized AI tools used for language learning is also noteworthy. Though few instruments fall under the category of evaluation tools (e.g., Gradescope), several have been used more than once, which is noteworthy.

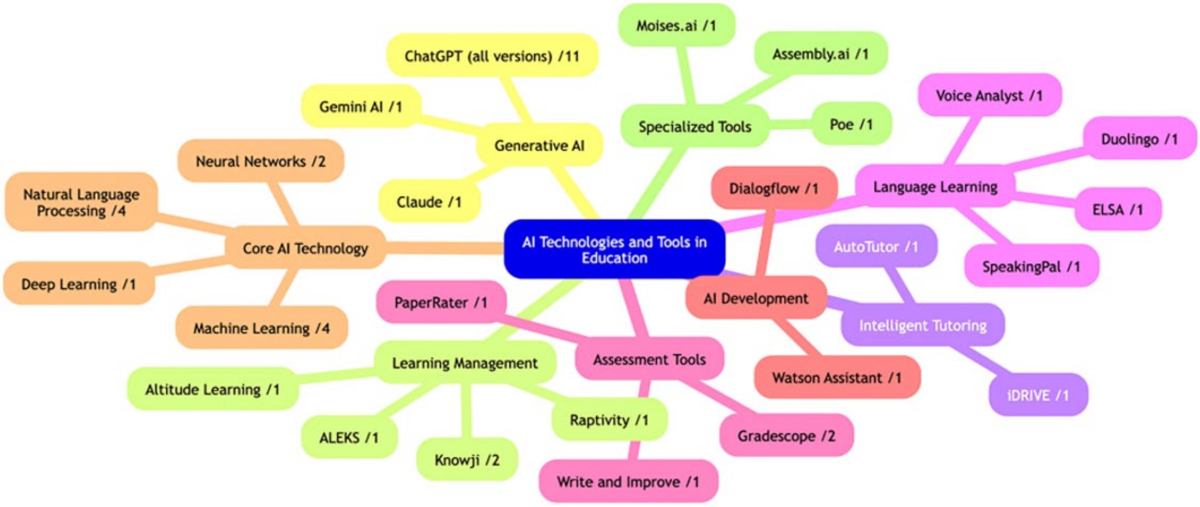

Figure 3. Used AI technologies and tools (the authors' own work)

General trends expose an amazing variety of applications of AI technology in education. While in certain categories less tools are employed, in others there is a great spectrum of tools. The predominance of GenAI and basic AI technologies suggests that these tools are preferred in education. In contrast, the limited use of specialized tools suggests that there is potential for further development in this area. The main use of ChatGPT suggests that similar GenAI tools could proliferate in the future rather extensively. The general application of simple AI technology implies that more specific educational uses in this field could be created. The variety of language learning and assessment instruments also suggests the possibility for more AI incorporation in these spheres.

According to the results of this study, AI technology application in personalized educational settings is growing and becoming more varied. This is the situation even if some technologies are more common than others. This is proof of the ongoing development in the field and suggests future chances for a fairer distribution of equipment.

Personalized Learning Theme

There were 5 categories under the theme of PL (**Table 2**). The first category is "learning design", which is found in a total of 12 studies. The code "adaptive content delivery" was found in 6 studies (S24, S09, S10, S29, S13, and S17). This code speaks of systems that dynamically modify instructional materials depending on demand from learners. The adaptability guarantees that material is pertinent and within each student's level and need. In research S13 the remark "the adaptability of pedagogical AI agent allows it to tailor its steps to deliver content to meet individual's learning needs and pace" supports this code. Customized learning paths (4 studies: S21, S08, S25, and S07) is mentioned in 4 studies. This involves creating individualized trajectories through learning material, allowing students to progress along personalized routes rather than following a standardized path. "This adaptability ensures that each learner is challenged appropriately, promoting engagement and facilitating deeper comprehension of the subject matter." It overlaps with the statement. Multimodal content Formats (2 studies: S09 and S10) code encompasses the provision of learning materials in various formats to accommodate different learning preferences and styles. For example, in study S09 "the learning objects are provided in different formats and media in order to meet the learning styles of each learner. These can be text documents (e.g., pdfs), presentations (e.g., PowerPoint slides), videos, etc." Virtual learning environments code refers to digital spaces that facilitate PL experiences through interactive and adaptable environments. (2 studies: S24 and S28) is mentioned in 2 studies. In one of these studies, S28, "ESCT-IoT intends to provide a PL environment that is both immersive and adaptable." This statement is mentioned.

The learner support category was obtained from 11 independent studies. There are 4 codes under this category. Found in six research (S24, S27, S02, S18, S23, and S01) the first one is the real-time feedback code. This algorithm allows constant learning adjustment by reflecting quick, customized answers to student actions

Table 2. Code and categories about personalized learning

Category	Code	Study IDs
Learning design	Adaptive content delivery	S24, S09, S10, S29, S13, S17
Learning design	Customized learning paths	S21, S08, S25, S07
Learning design	Multimodal content formats	S09, S10
Learning design	Virtual learning environments	S24, S28
Learner support	Real-time feedback	S24, S27, S02, S18, S23, S01
Learner support	Individual guidance	S14, S06, S01, S25
Learner support	Performance monitoring	S02, S15, S26
Learner support	Autonomous learning support	S12, S18
Learner characteristics	Learning style adaptation	S09, S10, S25
Learner characteristics	Prior knowledge assessment	S30, S19
Learner characteristics	Individual pace accommodation	S04, S01
Learner characteristics	Personal preferences	S30, S22
Technology integration	AI-enabled personalization	S03, S22, S05, S20
Technology integration	Chatbot integration	S27, S14, S06, S23
Technology integration	Smart learning systems	S10, S28
Technology integration	Data-driven adaptation	S15, S08
Learning outcomes	Performance improvement	S03, S26
Learning outcomes	Engagement enhancement	S30, S16, S26
Learning outcomes	Motivation increase	S30, S06
Implementation challenges	Standardization concerns	S11
Implementation challenges	Technical limitations	S18
Implementation challenges	Integration complexity	S05

and inputs. Providing customized advice and support, it functioned as a virtual co-teacher helping pupils feel supported and inspired all through the learning process. This quotation strengthens real-time commentary. Four studies feature other codes categorized as individual guidance (S14, S06, S01, and S25). This means customized mentoring and support geared to the needs and academic route of the student. "Designing chatbots that fit their specific learning goals and preferences helps students to increase their engagement and motivation, so generating more successful learning outcomes." S06 agrees with this. The performance Monitoring code was mentioned in 3 studies (S02, S15, and S26), and this code encompasses systems that track and analyze individual student progress and achievement. "Compared to more traditional, 'static' computer assisted learning approaches that deliver the same material to students of different knowledge and ability levels, the ITS approach is better because it can tailor educational content and instructional methods to each individual learner." The last code is autonomous learning support. It was supported by 2 studies (S12 and S18). This focuses on tools and approaches that facilitate independent learning while providing necessary guidance. Study (S18) stated "the AI chatbot, in turn, observes the learners' responses and generates subsequent feedback to better align with individual learning needs, creating a continuous feedback loop that fosters personalized learning experiences." He stated, as follows.

The third category is learner characteristics, which is a combination of 4 codes expressed in 8 studies. Learning style adaptation code is mentioned in 3 studies (S09, S10, and S25). This code represents systems that adjust to individual learning preferences and styles. S25 states "incorporating GenAI into language classrooms can enhance inclusivity and participation by tailoring language learning experiences to individual needs. GenAI's adaptive capabilities may enable PL paths, accommodating diverse learning styles and paces." The quote supports this. Two research reveal prior knowledge assessment codes (S30 and S19). This entails assessing and weighing students' current competency. The quote below helps to justify this. "Asset-based approaches consider the prior knowledge, resources, interests, and histories students bring to their learning environment in order to provide each learner relevant growth opportunities." (S19). Another code is individual pace accommodation and it is mentioned in 2 studies (S04 and S01). This code represents flexibility in learning speed and progression based on individual needs. "Thus, teachers learn the targeted content at their own pace, in their own space, and according to their own schedule." The quote is related to this code. Personal preferences was mentioned in 2 studies (S30 and S22). This encompasses systems that consider individual preferences in learning approaches and content delivery. "The adaptability of GenAI-based EdTech tools might facilitate PL journeys for students. Teachers can tailor content delivery to meet each student's unique needs by analyzing individual learning patterns and preferences." (S22) is associated with this code.

Table 3. Code and categories about pedagogical approaches

Category	Code	Study IDs
Adaptive learning systems & mechanisms	AI-driven content adaptation	S24, S09, S08, S20, S26
Adaptive learning systems & mechanisms	Dynamic learning pathways	S10, S21, S20
Adaptive learning systems & mechanisms	Personalized content delivery	S11, S09, S10, S22
Adaptive learning systems & mechanisms	Learning style-based instruction	S09, S26, S25
Interactive learning methods	Interactive learning activities	S04, S29, S22
Interactive learning methods	Interactive dialogue	S04, S27, S29, S15
Interactive learning methods	Collaborative learning	S15, S18, S13
Interactive learning methods	Student-centered learning	S18, S14, S25
Assessment and feedback	Automated assessment	S03, S02
Assessment and feedback	Formative assessment	S02, S22
Assessment and feedback	Real-time feedback	S04, S27, S23, S25
Assessment and feedback	Dynamic assessment	S21, S20
Instructional strategies	Multimodal teaching	S29, S22, S16
Instructional strategies	Blended learning	S07
Instructional strategies	Task-based learning	S06, S01
Instructional strategies	Practice-based learning	S14, S06
Instructional strategies	Self-directed learning support	S12, S06
Instructional strategies	Independent learning design	S12, S18
Instructional strategies	Guided autonomy framework	S12, S18, S05

Technology Integration category is mentioned in 8 studies and includes 3 codes. Chatbot Integration code is expressed in 4 studies (S27, S14, S06, and S23). For example, "ChatGPT can assist learners in developing language skills, such as writing and vocabulary acquisition, as well as providing personalized practice materials and explanations" in S27 supports this code. The smart learning systems code mentioned in two studies (S10 and S28) is expressed as "encompasses intelligent systems that adapt and respond to learner needs". In the S10 study, it is stated that "this paper proposes a design and modeling of an intelligent and dynamic adaptive learning system based on AI with the main objective of identifying and providing PL environments adapted to the learner needs." The statement is mentioned. The other code is data-driven adaptation and there are 2 studies (S15 and S08). This involves using learner data to inform and adjust learning experiences. The conclusion in study (S08) is "The system collects all users' information, such as preferences, knowledge level, need, goal, right or wrong answers, length of time in making decisions, and individual strategies throughout the learner's interaction with the system." It supports this.

The fifth category is learning outcomes and is found in 6 studies. The first code in the B category is performance improvement and is expressed in 2 studies (S03 and S26). This code represents measurable improvements in student achievement. S03 result "Personalized learning systems driven by AI have the potential to improve student performance by 30%." supports this. Three studies (S30, S16, and S26) have an engagement enhancing code. This entails higher student involvement in the learning process. This is supported in research S16 by the remark "GenAI can then be used to generate PL materials, adapting content to suit each student's needs". S30 and S06 have mentions of the code motivation increase. This rating reflects enhanced student motivation by means of individualized strategies. Because every student learns the content and conducts activities based on their own unique preferences, interests, degree of knowledge, skills, and ability, PL helps to raise the degree of motivation and involvement in the learning process. The quotation supports this code.

Pedagogical Approaches

Four key categories evolved from the research of pedagogical approaches in AI-supported learning environments: adaptive learning systems and mechanisms, interactive learning methods, assessment and feedback, and teaching strategies (**Table 3**). Every category includes special codes denoting different teaching strategies backed by different research.

Adaptive learning systems and mechanisms emerged as an important category reflecting the technological capacity of AI in education. Supported by five studies (S24, S09, S08, S20, and S26), AI-assisted content adaptation highlights how AI systems can modify and adjust learning content. It is especially clear that this is the case with the S26 approach, which "represents a methodological advance" by "using ML techniques to identify learning styles and adapt content." The utilization of variable learning paths is demonstrated by the dynamic learning routes developed in three different research (S10, S21, and S20). In accordance with S20: "AI holds the potential to construct learning paths that dynamically adapt to learners' progress, preferences, and challenges."

Personalized content delivery observed in four studies (S11, S09, S10, and S22) and learning type-based teaching revealed in three studies show even more the methodical approach toward individualism. S09's remark, "the learning objects are provided in different formats and media in order to meet the learning styles of each learner," captures this.

Among the many important categories that highlight the need for involvement and engagement is the category of interactive learning opportunities. Interactive learning activities and interactive discourse are two examples that demonstrate the shift toward active participation. Each of these strategies is supported by four separate research. As S04 notes, "engaging teachers in active learning is an indicator of the effectiveness of PD programs." Instead of passively watching or listening to someone lecturing, teachers were actively engaged with the materials." Cooperative learning in three studies (S15, S18, and S13) and student-centered learning in three studies (S18, S14, and S25) show the importance given to learner engagement. This is reflected in the finding of S25: "GenAI may help provide interactive and engaging language activities that cater to learners' different learning preferences."

Assessment and feedback emerged as a separate category that included a variety of approaches to assessment and response. Real-time feedback, supported by four studies (S04, S27, S23, and S25), represents the most frequently mentioned assessment approach. As highlighted in S23, "by simulating real conversation and providing immediate feedback, ChatGPT creates a one-of-a-kind opportunity for individualized language study." Automated assessment (S03 and S02), formative assessment (S02 and S22) and dynamic assessment (S21 and S20) illustrate different aspects of AI-supported assessment processes. S02 stresses that "students should get formative feedback on their built responses to help them to increase their capacity to offer explanations … The feedback should be customized to fit student needs if it is to be successful.

Traditional and AI-assisted approaches are among the several educational strategies included in the category. The analysis revealed several salient strategies: multimedia teaching (three studies: S29, S22, and S16), task-based learning (two studies: S06 and S01) and practice-based learning (two studies: S14 and S06). In addition, autonomous learning strategies such as self-directed learning support (S12 and S06), independent learning design (S12 and S18), and guided autonomy framework (three studies: S12, S18, and S05) were identified. This diversity is reflected in S05's observation: "The analyses also highlight the need for a balanced AI implementation that supports, not supplants, traditional educational methods."

Challenges

The thorough review revealed six main forms of difficulties using AI for individualized learning (**Table 4**). Technical challenges (f = 16) are the hardware, software, and infrastructure-related issues users and institutions run across implementing AI systems. Four main factors define this: system complexity and integration issues (f = 4), digital infrastructure limitations (f = 3), technical performance constraints (f = 3), and computational resource demands (f = 2). The complexity of implementation was particularly emphasized, as noted in S15: "A dialog between one agent and a human is relatively easy to implement but dual agents significantly increase the number of communications turns and possible sequences of speech acts." Infrastructure restrictions were also evident; S12 notes that "low digital literacy, older mobile phones and slow Internet might cause struggles navigating AFSs."

Data and privacy (f = 9) addresses issues with ethical usage, storage, protection, and collecting of student data in AI systems. Three key issues underline this category: ethical data use (f = 2), student data protection (f = 2), and data security and privacy (f = 5). This is especially underlined in S16: "These include data security, privacy concerns, bias in algorithms, equity and inclusivity, overreliance on technology, ethical use of data, technological literacy," says the statement. To further emphasize the need for privacy, S03 addresses "security and privacy issues related to the collection and use of student data by AI-based systems." "Pedagogical and implementation challenges" (f = 33) is a phrase that refers to the challenges that arise when trying to properly

Table 4. Code and categories about challenges

Category	Code	Study IDs
Technical challenges	System complexity and integration issues	S09, S15, S08, S26
Technical challenges	Digital infrastructure limitations	S12, S22, S20
Technical challenges	Technical performance limitations	S14, S06, S21
Technical challenges	Computational resource demands	S15, S26
Data and privacy	Data security and privacy concerns	S03, S22, S16, S20, S25
Data and privacy	Student data protection	S03, S16
Data and privacy	Ethical use of data	S16, S25
Pedagogical and implementation challenges	Limited social interaction	S08, S05, S17
Pedagogical and implementation challenges	Risk of reduced critical thinking	S05, S27
Pedagogical and implementation challenges	Overreliance on technology	S22, S13
Pedagogical and implementation challenges	Need for balanced implementation	S05, S20
Pedagogical and implementation challenges	Teacher training requirements	S30, S22, S20
Pedagogical and implementation challenges	Integration with existing systems	S09& S21
Pedagogical and implementation challenges	Lack of practical experience	S30, S13
Pedagogical and implementation challenges	Time management issues	S08, S06
Pedagogical and implementation challenges	Content validation requirements	S04, S17
Pedagogical and implementation challenges	Assessment accuracy	S18, S01
Pedagogical and implementation challenges	Plagiarism concerns	S27, S25
AI system limitations	Accuracy and reliability issues	S27, S12, S01, S17
AI system limitations	Limited response variety	S14, S23
AI system limitations	Algorithm transparency	S03, S20
AI system limitations	Content generation limitations	S17, S07
Access and equity issues	Uneven technology access	S24, S12
Access and equity issues	Digital literacy gaps	S12, S22
Access and equity issues	Cost and resource barriers	S12, S26
Access and equity issues	Algorithm bias issues	S16, S19
Access and equity issues	Access disparities	S29, S19
Access and equity issues	Cultural localization needs	S22, S16
Methodological challenges	Sample size limitations	S02, S01
Methodological challenges	Limited study duration	S06, S01
Methodological challenges	Methodology constraints	S04, S10

incorporate AI into educational practices and ensuring that it is aligned with the core principles of teaching and learning.

Comprising several facets of educational implementation, this category stood as the most difficult set of obstacles. This included worries about less social connection (f = 2), lower critical thinking (f = 2), and the necessity of a balanced implementation (f = 2). As S30 notes, "there is no overall planning that would be based on theories of using AI in higher education and a shortage of qualified teachers who could apply AI-based systems in their teaching practice." For the purposes of teacher preparation, this presented a significant challenge. With S25 observing, "concerns were raised regarding the possible risks associated with students' inclination toward plagiarism," plagiarism problems also surfaced clearly.

AI system limitations (f = 12) means the current technological limitations and inadequacy of AI systems to meet educational needs. The four main topics were the emphasis of this category: accuracy and dependability problems (f = 4), limited response diversity (f = 2), algorithm transparency (f = 2), and content generating constraints (f = 2). As pointed out in S23: "One major issue is the possible for ChatGPT's responses to lack of nuanced knowledge and contextual awareness, which could lead to errors or misinterpretation of users' input."

Access and equity Issues addresses the challenges of ensuring fair and equal access to AI-enhanced educational opportunities across several demographic groups and contexts using f = 18. This group included unequal technology access (f = 2), digital literacy gaps (f = 2), cost constraints (f = 2), algorithm bias (f = 2), access discrepancies (f = 2), and cultural localization needs (f = 2). This was particularly emphasized in S29: "it is imperative to navigate the complexities surrounding issues of social justice, notably the disparities in access to cutting-edge technologies across diverse educational settings."

Methodological challenges (f = 9) refers to the research-related difficulties in studying and evaluating the effectiveness of AI in educational settings. Research-related problems like sample size restrictions (f = 2), limited study time (f = 2), and technique restrictions (f = 2) dominated this category. As S06 notes, "the intervention duration in this study was relatively short, consisting of only a 1.5-h workshop where students utilized their self-made chatbots for a single writing task."

All told, it identified 97 difficult situations in all three categories. Technical challenges (16%), AI system limitations (12%), data and privacy and methodological challenges were the most often mentioned concerns; followed by pedagogical and implementation challenges (34%), and access and equity issues (19%), each representing roughly 9% of the total challenges identified.

DISCUSSION

What Are the Methodological Characteristics (Research Area, Method, and Sample) of Artificial Intelligence-Supported Personalized Learning Studies?

Analyzing the whole research findings will enable you to identify numerous fairly significant trends and patterns. Examining the research, scientists concentrated particularly on language instruction (9) and general education (11). This focus in the field of general education could be the outcome of researchers focusing on studies aimed at revealing the general attitudes of the subjects instead of experimental ones. This tendency fits the results of Zawacki-Richter et al. (2019), who underlined that the studies are largely exploratory in character and that the usage of AI applications in education is still in the maturation stage.

The prominence of studies in the field of language education can be attributed to the fact that large language models are primarily capable of producing English text and audio. As Li and Wong (2023) state, the potential of general language models, especially ChatGPT, in developing English language skills may have led researchers to this field.

Analysis of methodological preferences reveals that with 15 studies, mixed method approach is the most often used study design. Four studies in quantitative research and seven studies in qualitative research follow here. This dispersion could suggest that tailored learning research backed by AI is still in its early years. Bernacki et al. (2021) stated that the studies in this field are generally exploratory and pilot studies, so a mixed method approach is preferred.

In terms of sample characteristics, it is seen that pilot applications were conducted with small groups in most of the studies. The fact that sample sizes vary widely between 5 and 607, but mostly with small groups indicates that the field is still developing and researchers prefer to start with pilot studies before large-scale applications. Tetzlaff et al. (2021) emphasized that small-scale pilot studies in AI-supported PL research are important to identify potential problems in the implementation process and to develop solutions.

What Are the Roles of Artificial Intelligence in Personalized Learning Settings?

When the findings on the educational roles of AI and the technologies used are examined, it is seen that there is a significant gap between technological capacity and practical application. In particular, despite the widespread use of general-purpose AI technologies (ChatGPT and ML), the limited use of specialized educational tools is noteworthy. Lan and Chen (2024) assert that although the application of AI in PL is still in its early years and that the technologies we now have cannot completely meet the demands of education. Shankar et al. (2024) argue that more research and development on how to match these technologies to educational goals is required. This is particularly true in relation to the extensive application of big language models in education.

The predominance of "personalization mechanisms" and "interactive support features" in the categories connected to the roles of AI, but limited application in areas such "user interface customization" and "assessment generation" show that the technological potential has not been totally used. Kim (2024) states that this situation constitutes a significant limitation especially in PL processes and that customized solutions are needed for more effective use of existing AI technologies in educational contexts. The balanced distribution of the "learning process support" category implies that in the future AI can be included into the learning procedure more holistically. Still, it seems that to realize this potential we need to improve the technological infrastructure and learning resources. Particularly with regard to PL systems, Seo et al. (2024) and Ayeni et al. (2024) argue that technology developers and educators should cooperate more closely if we are to maximize AI technologies. They also argue that while developing answers, one should consider their educational requirements.

What Are the Pedagogical Approaches Used in Artificial Intelligence-Supported Personalized Learning Settings?

The results on pedagogical approaches and individualized learning expose significant junction of technological adaptation and pedagogical integration. Particularly the high frequency of “AI-driven content adaptation” (5 studies) and “adaptive content distribution” (6 studies) codes show the key component of technology-driven adaptation in PL. Lippert et al. (2020) do indeed claim that by assessing student profiles, AI-driven adaptive systems offer tailored material delivery. In line with this, Kaouni et al. (2023) underline that AI-based adaptive learning systems may dynamically modify learning environments depending on the demands of the learners.

An analysis of six “real-time feedback” research and four “interactive dialogue” studies reveals the efficacy of interactive technology and rapid feedback in providing students with personalized assistance through customization. Sachete et al. (2024) emphasize the customization of learner-system interaction in adaptive learning systems, while Villegas-Ch et al. (2024) emphasize the ability of ML models to alter instructional content according to learning styles. These findings augment those of Bernacki et al. (2021) about the characteristics of interaction and feedback in PL.

In terms of instructional strategies and learner characteristics, learner-centered methodologies and designs attuned to individual variances are particularly prominent in both domains. The use of AI chatbots to facilitate responsive teaching approaches in mathematics education was demonstrated by Lee and Yeo (2022), while Guo and Li (2024) examined students’ use of AI chatbots for personalized writing assistance. These studies demonstrate the effectiveness of technology-enabled personalization in fostering student agency.

Within the context of assessment and feedback systems, formative remarks and continuous assessment are emphasized as crucial components. Ariely et al. (2024) looked into the potential of AI-assisted assessment systems to provide individualized comments in biology classes, and Naz and Robertson (2024) evaluated ChatGPT’s effectiveness in PFS. These findings augment those of Tetzlaff et al. (2021) regarding the crucial role of evaluation and feedback mechanisms in personalized education.

The results also underscore specific challenges associated with the integration of technology and education. Shankar et al. (2024) highlight the challenges teachers have in integrating AI technology into pedagogical methods, while Kucirkova and Leaton Gray (2023) discuss the limitations of incorporating AI-powered systems inside democratic learning environments. The findings indicate a necessity for more research and practical studies to effectively integrate individualized learning and pedagogical methods in technology-enhanced education.

What Are the Challenges and Limitations Encountered in Artificial Intelligence Personalized Learning Applications?

Analyzing difficulties in AI-supported PL systems exposes the most typically occurring category: pedagogical and implementation problems. This suggests that educational integration is a more diverse and variegated process than technical integration. Emphasizing that pedagogical adaptation is more difficult than technological adaptation, Mondal et al. (2023) investigated the challenges teachers experience using AI technologies for instructional reasons. Comparatively, Tapalova and Zhiyenbayeva (2022) said that the application of AI in building customized learning paths demands for a reconfiguration of educational methods rather than technological competencies.

Technical challenges and data-privacy issues also stand out as significant barriers. In particular, system complexity and integration issues and data security and privacy concerns are the most frequently reported challenges. Villegas-Ch et al. (2024) examined the technical difficulties encountered in the process of adapting ML models’ educational content to individual learning styles, while Zhou (2023) emphasized the critical importance of data security and privacy issues in the use of AI in higher education. Concerns about the moral use of student data are a major obstacle for the deployment of AI-driven PL solutions (Baltezarevič & Baltezarevič, 2024).

Overcoming these challenges requires a comprehensive and focused approach. The research by Shankar et al. (2024) stresses the significance of obtaining technical as well as educational capacities. Teachers also have enormous challenges bringing AI into the learning process. Effective integration, according to Yeh (2024), calls for institutional capacity building and systematic support systems. This is something he came onto when researching joint use of GenAI and inquiry-based learning. Based on these findings, it is clear that in order to ensure the success of PL apps that are backed by AI, it is necessary to take into consideration the investments in technological infrastructure, the training of teachers, and the policies of institutions.

CONCLUSION

This systematic literature review aimed to comprehensively examine the current state of AI-supported PL applications, pedagogical approaches and challenges. The prominence of general education and language education in the field distribution of the reviewed studies indicates that AI technologies are more widely used in these fields. Particularly the extensive usage of big language models like ChatGPT and ML technology exposes how limited AI applications in education are based on general purpose tools.

Analyzing the educational responsibilities of AI reveals adaptive material delivery and automatic feedback systems as particularly noteworthy. Customized learning strategies emphasizing learner characteristics and needs help to support these roles. Regarding educational strategies, interactive learning systems and adaptive learning tools find great application. This underlines the importance of technology-supported personalization grounded on educational principles.

Analyzing the difficulties faced reveals that pedagogical and implementation issues predominate over technological ones. Particularly noteworthy as major challenges are teacher preparation requirements, system integration and content validation need. Often cited difficulties are also privacy and data security issues. Technical, educational, and ethical aspects must all be addressed holistically if we are to overcome these obstacles.

Recommendations

In line with the findings of the research, the following recommendations can be made: First of all, AI tools specific to educational needs should be developed and disseminated. Comprehensive professional development programs should be designed to improve both technical and pedagogical competencies of teachers. At the institutional level, data security and ethical use policies should be developed and investments in technical infrastructure should be increased. At the research level, there is a need to identify solution strategies that are effective in different contexts, document good practice examples and monitor long-term impacts. Especially, research areas with highest priority are assessing the effects on learning outcomes and creating scalable implementation approaches.

In terms of implementation, institutions should first establish a strong technical infrastructure and clearly define data security policies. Regular training and mentoring programs should be organized for teachers to use AI tools effectively, and professional learning communities should be established where good practices can be shared. Orientation programs for students should be organized, technical support should be provided and regular feedback should be received. In addition, regular evaluations should be conducted to ensure the quality of the process, learning analytics should be used effectively and feedback mechanisms should be established for continuous improvement. This holistic approach will ensure the successful implementation of AI-supported PL in educational institutions.

Limitations

This research has certain restrictions. First, the fact that only English-language publications were considered and that the examined studies span the years 2010 to 2024 could have resulted in several significant studies being omitted. Second, most of the studies being small-scale pilot programs conducted largely in higher education restrict the generalizability of the outcomes. Moreover, given the rapid development of AI technology, some existing techniques and problems might not yet be reflected in literature.

These limitations can be surmounted in forthcoming studies including several educational levels and larger samples with a broader temporal range and language variety.

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REFERENCES

Abbas, N., Ali, I., Manzoor, R., Hussain, T., & Hussain, M. H. A. I. (2023). Role of artificial intelligence tools in enhancing students' educational performance at higher levels. *Journal of Artificial Intelligence, Machine Learning and Neural Network, 3*(5), 36–49. https://doi.org/10.55529/jaimlnn.35.36.49

Abulibdeh, A., Zaidan, E., & Abulibdeh, R. (2024). Navigating the confluence of artificial intelligence and education for sustainable development in the era of industry 4.0: Challenges, opportunities, and ethical dimensions. *Journal of Cleaner Production, 437*, Article 140527. https://doi.org/10.1016/j.jclepro.2023.140527

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

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

Al-Badi, A., Khan, A., & Eid-Alotaibi. (2022). Perceptions of learners and instructors towards artificial intelligence in personalized learning. *Procedia Computer Science, 201*(C), 445–451. https://doi.org/10.1016/j.procs.2022.03.058

Albdrani, R. N., & Al-Shargabi, A. A. (n. d.). Investigating the effectiveness of ChatGPT for providing personalized learning experience: A case study. *International Journal of Advanced Computer Science and Applications, 14*(11). https://doi.org/10.14569/IJACSA.2023.01411122

Alenezi, A. (2023). Personalized learning strategies in higher education in Saudi Arabia: Identifying common approaches and conditions for effective implementation. *TEM Journal, 12*(4), 2023–2037. https://doi.org/10.18421/TEM124-13

Al-Zyoud, H. M. M. (2020). The role of artificial intelligence in teacher professional development. *Universal Journal of Educational Research, 8*(11B), 6263–6272. https://doi.org/10.13189/ujer.2020.082265

Ariely, M., Nazaretsky, T., & Alexandron, G. (2024). Causal-mechanical explanations in biology: Applying automated assessment for personalized learning in the science classroom. *Journal of Research in Science Teaching, 61*(8), 1858–1889. https://doi.org/10.1002/tea.21929

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

Bahroun, Z., Anane, C., Ahmed, V., & Zacca, A. (2023). Transforming education: A comprehensive review of generative artificial intelligence in educational settings through bibliometric and content analysis. *Sustainability, 15*(17), Article 12983. https://doi.org/10.3390/su151712983

Baltezarević, R., & Baltezarević, I. (2024). Students' attitudes on the role of artificial intelligence (AI) in personalized learning. *International Journal of Cognitive Research in Science, Engineering and Education, 12*(2), 123–145. https://doi.org/10.23947/2334-8496-2024-12-2-387-397

Bayly-Castaneda, K., Ramirez-Montoya, M. S., & Morita-Alexander, A. (2024). Crafting personalized learning paths with AI for lifelong learning: A systematic literature review. *Frontiers in Education, 9*. https://doi.org/10.3389/feduc.2024.1424386

Bernacki, M. L., Greene, M. J., & Lobczowski, N. G. (2021). A systematic review of research on personalized learning: Personalized by whom, to what, how, and for what purpose(s)? *Educational Psychology Review, 33*(4), 1675–1715. https://doi.org/10.1007/s10648-021-09615-8

Bhutoria, A. (2022). Personalized education and artificial intelligence in the United States, China, and India: *A systematic review using a human-in-the-loop model*. *Computers and Education: Artificial Intelligence, 3*, Article 100068. https://doi.org/10.1016/j.caeai.2022.100068

Bingham, A. J., Pane, J. F., Steiner, E. D., & Hamilton, L. S. (2018). Ahead of the curve: Implementation challenges in personalized learning school models. *Educational Policy, 32*(3), 454–489. https://doi.org/10.1177/0895904816637688

Bondie, R. (2023). Exploring personalized learning and open education pedagogy in multilingual learner teacher preparation. *Online Learning Journal, 27*(4), 315–347. https://doi.org/10.24059/olj.v27i4.4018

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology, 3*(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Castro, G. P. B., Chiappe, A., Rodríguez, D. F. B., & Sepulveda, F. G. (2024). Harnessing AI for Education 4.0: Drivers of personalized learning. *Electronic Journal of E-Learning, 22*(5), 1–14. https://doi.org/10.34190/ejel.22.5.3467

Cheng, J., & Wang, H. (2021). Adaptive algorithm recommendation and application of learning resources in English fragmented reading. *Complexity*. https://doi.org/10.1155/2021/5592534

Copur-Gencturk, Y., Li, J., & Atabas, S. (2024). Improving teaching at scale: Can AI be incorporated into professional development to create interactive, personalized learning for teachers? *American Educational Research Journal, 61*(4), 767–802. https://doi.org/10.3102/00028312241248514

Creswell, J. W., & Clark, V. L. P. (2017). *Designing and conducting mixed methods research*. SAGE.

Duran, V. (2024). Analyzing teacher candidates' arguments on AI integration in education via different chatbots. *Digital Education Review, 45*, 68–83. https://doi.org/10.1344/der.2024.45.68-83

El-Sabagh, H. A. (2021). Adaptive e-learning environment based on learning styles and its impact on development students' engagement. *International Journal of Educational Technology in Higher Education, 18*, Article 53. https://doi.org/10.1186/s41239-021-00289-4

Fadieieva, L. O. (2023). Adaptive learning: A cluster-based literature review (2011-2022). *Educational Technology Quarterly, 2023*(3), 319–366. https://doi.org/10.55056/etq.613

Fissore, C., Floris, F., Conte, M. M., & Sacchet, M. (2024). Teacher training on artificial intelligence in education. In D. G. Sampson, D. Ifenthaler, & P. Isaías (Eds.), *Smart learning environments in the post pandemic era. Cognition and exploratory learning in the digital age* (pp. 227–244). Springer. https://doi.org/10.1007/978-3-031-54207-7_13

Forman, J., & Damschroder, L. (2007). Qualitative content analysis. In L. Jacoby, & L. Siminoff (Eds.), *Empirical methods for bioethics: A primer* (pp. 39–62). Emerald Group Publishing Limited. https://doi.org/10.1016/S1479-3709(07)11003-7

Guettala, M., Bourekkache, S., Kazar, O., & Harous, S. (2024). Generative artificial intelligence in education: Advancing adaptive and personalized learning. *Acta Informatica Pragensia, 13*(3), 460–489. https://doi.org/10.18267/j.aip.235

Guo, K., & Li, D. (2024). Understanding EFL students' use of self-made AI chatbots as personalized writing assistance tools: A mixed methods study. *System, 124*, 103362. https://doi.org/10.1016/j.system.2024.103362

Hang, C. N., Wei Tan, C., & Yu, P. D. (2024). MCQGen: A large language model-driven MCQ generator for personalized learning. *IEEE Access, 12*, 102261–102273. https://doi.org/10.1109/ACCESS.2024.3420709

Harati, H., Sujo-Montes, L., Tu, C.-H., Armfield, S. J. W., Yen, C.-J., & Edu, S. A. (2021). Assessment and learning in knowledge spaces (ALEKS) adaptive system impact on students' perception and self-regulated learning skills. *Education Sciences, 11*(10), Article 603. https://doi.org/10.3390/educsci11100603

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

Kaiss, W., Mansouri, K., & Poirier, F. (2023). Effectiveness of an adaptive learning chatbot on students' learning outcomes based on learning styles. *International Journal of Emerging Technologies in Learning, 18*(13), 250–261. https://doi.org/10.3991/ijet.v18i13.39329

Kaouni, M., Lakrami, F., & Labouidya, O. (2023). The design of an adaptive e-learning model based on artificial intelligence for enhancing online teaching. *International Journal of Emerging Technologies in Learning, 18*(6), 202–219. https://doi.org/10.3991/ijet.v18i06.35839

Katiyar, N., Khare, M. D., Kumar, J., Sharma, A., Rawat, S., & Srivastav, J. (2024). Intelligent e-learning platform consolidating Web of Things and ChatGPT. In N. Goel, & P. K. Yadav (Eds.), *Internet of things enabled machine learning for biomedical applications* (pp. 202–221). CRC Press. https://doi.org/10.1201/9781003487647-12

Katsamakas, E., Pavlov, O. V., & Saklad, R. (2024). Artificial intelligence and the transformation of higher education institutions: A systems approach. *Sustainability, 16*(14), Article 6118. https://doi.org/10.3390/su16146118

Khor, E. T., & K, M. (2024). A systematic review of the role of learning analytics in supporting personalized learning. *Education Sciences, 14*(1), Article 51. https://doi.org/10.3390/educsci14010051

Kim, J. (2024). Leading teachers' perspective on teacher-AI collaboration in education. *Education and Information Technologies, 29*(7), 8693–8724. https://doi.org/10.1007/s10639-023-12109-5

Klašnja-Milićević, A., Vesin, B., Ivanović, M., & Budimac, Z. (2011). E-learning personalization based on hybrid recommendation strategy and learning style identification. *Computers and Education, 56*(3), 885–899. https://doi.org/10.1016/j.compedu.2010.11.001

Köbis, L., & Mehner, C. (2021). Ethical questions raised by AI-supported mentoring in higher education. *Frontiers in Artificial Intelligence, 4*. https://doi.org/10.3389/frai.2021.624050

Kochmar, E., Vu, D. Do, Belfer, R., Gupta, V., Serban, I. V., & Pineau, J. (2022). Automated data-driven generation of personalized pedagogical interventions in intelligent tutoring systems. *International Journal of Artificial Intelligence in Education, 32*(2), 323–349. https://doi.org/10.1007/s40593-021-00267-x

Krippendorff, K. (2018). *Content analysis: An introduction to its methodology*. SAGE. https://doi.org/10.4135/9781071878781

Kucirkova, N., & Leaton Gray, S. (2023). Beyond personalization: Embracing democratic learning within artificially intelligent systems. *Educational Theory, 73*(4), 469–489. https://doi.org/10.1111/edth.12590

Kwak, Y., Ahn, J. W., & Seo, Y. H. (2022). Influence of AI ethics awareness, attitude, anxiety, and self-efficacy on nursing students' behavioral intentions. *BMC Nursing, 21*, Article 267. https://doi.org/10.1186/s12912-022-01048-0

Lan, Y. J., & Chen, N. S. (2024). Teachers' agency in the era of LLM and generative AI: Designing pedagogical AI agents. *Educational Technology and Society, 27*(1), 1–17.

Lee, D., & Yeo, S. (2022). Developing an AI-based chatbot for practicing responsive teaching in mathematics. *Computers and Education, 191*, Article 104646. https://doi.org/10.1016/j.compedu.2022.104646

Li, K. C., & Wong, B. T. M. (2023). Artificial intelligence in personalised learning: A bibliometric analysis. *Interactive Technology and Smart Education, 20*(3), 422–445. https://doi.org/10.1108/ITSE-01-2023-0007

Li, L., & Kim, M. (2024). It is like a friend to me: Critical usage of automated feedback systems by self-regulating English learners in higher education. *Australasian Journal of Educational Technology, 40*(1), 1–18. https://doi.org/10.14742/ajet.8821

Li, Y. (2024). The digital transformation of college English classroom: Application of artificial intelligence and data science. *ICST Transactions on Scalable Information Systems, 11*(5). https://doi.org/10.4108/eetsis.5636

Lippert, A., Shubeck, K., Morgan, B., Hampton, A., & Graesser, A. (2020). Multiple agent designs in conversational intelligent tutoring systems. *Technology, Knowledge and Learning, 25*(3), 443–463. https://doi.org/10.1007/s10758-019-09431-8

Liu, J. (2024). Enhancing English language education through big data analytics and generative AI. *Journal of Web Engineering, 23*(2), 227–250. https://doi.org/10.13052/jwe1540-9589.2322

Ma, D., Akram, H., & Chen, I.-H. (2024). Artificial intelligence in higher education: A cross-cultural examination of students' behavioral intentions and attitudes. *International Review of Research in Open and Distributed Learning, 25*(3), 134–157. https://doi.org/10.19173/irrodl.v25i3.7703

Mahmudi, A. A., Fionasari, R., Mardikawati, B., & Judijanto, L. (2023). Integration of artificial intelligence technology in distance learning in higher education. *Journal of Social Science Utilizing Technology, 1*(4), 190–201. https://doi.org/10.70177/jssut.v1i4.661

Maier, U., & Klotz, C. (2022). Personalized feedback in digital learning environments: Classification framework and literature review. *Computers and Education: Artificial Intelligence, 3*, Article 100080. https://doi.org/10.1016/j.caeai.2022.100080

Miles, M. B., & Huberman, A. M. (1994). *Qualitative data analysis: An expanded sourcebook*. SAGE.

Miles, M. B., Huberman, A. M., & Saldann, J. (2014). *Qualitative data analysis: A methods sourcebook*. SAGE.

Mondal, H., Marndi, G., Behera, J. K., & Mondal, S. (2023). ChatGPT for teachers: Practical examples for utilizing artificial intelligence for educational purposes. *Indian Journal of Vascular and Endovascular Surgery, 10*(3), 200–205. https://doi.org/10.4103/ijves.ijves_37_23

Moya, S., & Camacho, M. (2024). Leveraging AI-powered mobile learning: A pedagogically informed framework. *Computers and Education: Artificial Intelligence, 7*, Article 100276. https://doi.org/10.1016/j.caeai.2024.100276

Namaziandost, E., & Rezai, A. (2024). Special issue: Artificial intelligence in open and distributed learning: Does it facilitate or hinder teaching and learning? *International Review of Research in Open and Distributed Learning, 25*(3), i–vii. https://doi.org/10.19173/irrodl.v25i3.8070

Naz, I., & Robertson, R. (2024). Exploring the feasibility and efficacy of ChatGPT3 for personalized feedback in teaching. *Electronic Journal of E-Learning, 22*(2), 98–111. https://doi.org/10.34190/ejel.22.2.3345

Newman, M., & Gough, D. (2020). Systematic reviews in educational research: Methodology, perspectives and application. In O. Zawacki-Richter, M. Kerres, S. Bedenlier, M. Bond, & K. Buntins (Eds.), *Systematic reviews in educational research: Methodology, perspectives and application* (pp. 3–22). Springer. https://doi.org/10.1007/978-3-658-27602-7_1

Ocumpaugh, J., Roscoe, R. D., Baker, R. S., Hutt, S., & Aguilar, S. J. (2024). Toward asset-based instruction and assessment in artificial intelligence in education. *International Journal of Artificial Intelligence in Education, 34*, 1559–1598. https://doi.org/10.1007/s40593-023-00382-x

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., ..., & Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ, 372*, Article n71. https://doi.org/10.1136/bmj.n71

Peng, H., Ma, S., & Spector, J. M. (2019). Personalized adaptive learning: An emerging pedagogical approach enabled by a smart learning environment. *Smart Learning Environments, 6*, Article 9. https://doi.org/10.1186/s40561-019-0089-y

Pesovski, I., Santos, R., Henriques, R., & Trajkovik, V. (2024). Generative AI for customizable learning experiences. *Sustainability, 16*(7), Article 3034. https://doi.org/10.3390/su16073034

Radif, M., & Hameed, O. M. (2024). AI-driven innovations in e-learning: Transforming educational paradigms for enhanced learning outcomes. *Artseduca, 2024*(38), 404–414.

Roshanaei, M., Olivares, H., & Lopez, R. R. (2023). Harnessing AI to foster equity in education: Opportunities, challenges, and emerging strategies. *Journal of Intelligent Learning Systems and Applications, 15*(04), 123–143. https://doi.org/10.4236/jilsa.2023.154009

Russell, S. J., & Norvig, P. (2016). *Artificial intelligence: A modern approach*. Pearson.

Sachete, A. d. S., de Sant'anna de Freitas Loiola, A. V., & Gomes, R. S. (2024). AdaptiveGPT: Towards intelligent adaptive learning. *Multimedia Tools and Applications, 83*, 89461–89477. https://doi.org/10.1007/s11042-024-20144-8

Sajja, R., Sermet, Y., Cikmaz, M., Cwiertny, D., & Demir, I. (2024). Artificial intelligence-enabled intelligent assistant for personalized and adaptive learning in higher education. *Information, 15*(10), Article 596. https://doi.org/10.3390/info15100596

Sayed, W. S., Noeman, A. M., Abdellatif, A., Abdelrazek, M., Badawy, M. G., Hamed, A., & El-Tantawy, S. (2023). AI-based adaptive personalized content presentation and exercises navigation for an effective and engaging e-learning platform. *Multimedia Tools and Applications, 82*(3), 3303–3333. https://doi.org/10.1007/s11042-022-13076-8

Seo, K., Yoo, M., Dodson, S., & Jin, S. H. (2024). Augmented teachers: K-12 teachers' needs for artificial intelligence's complementary role in personalized learning. *Journal of Research on Technology in Education*. https://doi.org/10.1080/15391523.2024.2330525

Shankar, S. K., Pothancheri, G., Sasi, D., & Mishra, S. (2024). Bringing teachers in the loop: Exploring perspectives on integrating generative AI in technology-enhanced learning. *International Journal of Artificial Intelligence in Education*. https://doi.org/10.1007/s40593-024-00428-8

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

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

Slamet, J. (2024). Potential of ChatGPT as a digital language learning assistant: EFL teachers' and students' perceptions. *Discover Artificial Intelligence, 4*, Article 46. https://doi.org/10.1007/s44163-024-00143-2

Soler Costa, R., Tan, Q., Pivot, F., Zhang, X., & Wang, H. (2021). Personalized and adaptive learning. *Texto Livre: Linguagem e Tecnologia, 14*(3), Article e33445. https://doi.org/10.35699/1983-3652.2021.33445

Tang, X., Chen, Y., Li, X., Liu, J., & Ying, Z. (2019). A reinforcement learning approach to personalized learning recommendation systems. *British Journal of Mathematical and Statistical Psychology, 72*(1), 108–135. https://doi.org/10.1111/bmsp.12144

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

Tetzlaff, L., Schmiedek, F., & Brod, G. (2021). Developing personalized education: A dynamic framework. *Educational Psychology Review, 33*(3), 863–882). https://doi.org/10.1007/s10648-020-09570-w

Tonbuloğlu, B. (2023). An evaluation of the use of artificial intelligence applications in online education. *Journal of Educational Technology and Online Learning, 6*(4), 866–884. https://doi.org/10.31681/jetol.1335906

Tsamados, A., Aggarwal, N., Cowls, J., Morley, J., Roberts, H., Taddeo, M., & Floridi, L. (2022). The ethics of algorithms: Key problems and solutions. *AI and Society, 37*(1), 215–230. https://doi.org/10.1007/s00146-021-01154-8

Ulla, M. B., Advincula, M. J. C., Mombay, C. D. S., Mercullo, H. M. A., Nacionales, J. P., & Entino-Señorita, A. D. (2024). How can GenAI foster an inclusive language classroom? A critical language pedagogy perspective from Philippine university teachers. *Computers and Education: Artificial Intelligence, 7*, Article 100314. https://doi.org/10.1016/j.caeai.2024.100314

Usak, M. (2024). Artificial intelligence in biology education. *Journal of Baltic Science Education, 23*(5), 806–808. https://doi.org/10.33225/jbse/24.23.806

Villegas-Ch, W., Garcia-Ortiz, J., & Sanchez-Viteri, S. (2024). Personalization of learning: Machine learning models for adapting educational content to individual learning styles. *IEEE Access, 12*, 121114–121130. https://doi.org/10.1109/ACCESS.2024.3452592

Walkington, C., & Bernacki, M. L. (2020). Appraising research on personalized learning: Definitions, theoretical alignment, advancements, and future directions. *Journal of Research on Technology in Education, 52*(3), 235–252. https://doi.org/10.1080/15391523.2020.1747757

Wu, R., & Yu, Z. (2024). Do AI chatbots improve students learning outcomes? Evidence from a meta-analysis. *British Journal of Educational Technology, 55*(1), 10–33. https://doi.org/10.1111/bjet.13334

Xiao, Y., & Watson, M. (2019). Guidance on conducting a systematic literature review. *Journal of Planning Education and Research, 39*(1), 93–112. https://doi.org/10.1177/0739456X17723971

Xiao, Y., & Zhi, Y. (2023). An exploratory study of EFL learners' use of ChatGPT for language learning tasks: Experience and perceptions. *Languages, 8*(3), Article 212. https://doi.org/10.3390/languages8030212

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 and Education, 140*, Article 103599. https://doi.org/10.1016/j.compedu.2019.103599

Xie, J. X. (2024). Research on the reform of university education and teaching mode driven by artificial intelligence. *International Journal for Multidisciplinary Research, 6*(3). https://doi.org/10.36948/ijfmr.2024.v06i03.23245

Yan, L., Greiff, S., Teuber, Z., & Gašević, D. (2024). Promises and challenges of generative artificial intelligence for human learning. *Nature Human Behaviour, 8*(10), 1839–1850. https://doi.org/10.1038/s41562-024-02004-5

Yang, C. C. Y., & Ogata, H. (2023). Personalized learning analytics intervention approach for enhancing student learning achievement and behavioral engagement in blended learning. *Education and Information Technologies, 28*(3), 2509–2528. https://doi.org/10.1007/s10639-022-11291-2

Yeh, H. C. (2024). The synergy of generative AI and inquiry-based learning: Transforming the landscape of English teaching and learning. *Interactive Learning Environments, 11*(5). https://doi.org/10.1080/10494820.2024.2335491

Yılmaz, Ö. (2024). Personalised learning and artificial intelligence in science education: Current state and future perspectives. *Educational Technology Quarterly, 2024*(3), 255–274. https://doi.org/10.55056/etq.744

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*, Article 39. https://doi.org/10.1186/s41239-019-0171-0

Zhou, C. (2023). Integration of modern technologies in higher education on the example of artificial intelligence use. *Education and Information Technologies, 28*(4), 3893–3910. https://doi.org/10.1007/s10639-022-11309-9