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TRENDS AND CHALLENGES IN PERSONALIZING LEARNING CONTENT FOR STUDENTS USING ARTIFICIAL INTELLIGENCE

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Abstract. Artificial intelligence-based solutions are widely used in different areas. With the advent of chatGPT, education has faced many challenges, such as student cheating by generating text in various practical and assessment tasks. As the number of large language models increases, it becomes difficult to control their use, and their capabilities increase over time as well. However, large language models do not only provide a negative aspect, but when used properly, they can be applied to useful and meaningful solutions. One of these is the personalization of learning, which would help to direct learning to the right needs without much human intervention, for example, when there are certain difficulties, knowledge gaps or lack of motivation. This manuscript, using a systematic analysis of the scientific literature, reviews technological solutions that are already currently used in personalizing learning. It also reviews the latest trends and challenges that would allow this area to be raised to a higher level.

Keywords: personalized learning, educational content, students, artificial intelligence, NLP, LLMs.

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1. Introduction

Learning is an integral part of every person's life and indeed a lifelong process. More structured learning begins in the early years when people start attending school, then continues at colleges or universities, and, after graduation, is expected to continue as both a lifelong and life-wide process (Johri, 2022). According to Jørgensen and Brogaard et al. (2021), each student comes from a different background, with different knowledge, experiences, and learning styles. Meanwhile, teachers usually rely on the learning styles that are most familiar to themselves and on the assumption that students already have a certain common knowledge base. Learning strategies are often based on general indicators that do not always reflect the needs or abilities of all students (Sugano & Mamolo, 2021). Therefore, students who have a smaller knowledge base or a different learning style often experience difficulties in comprehending new information (El-Sabagh, 2021). This leads not only to poor learning outcomes but also to a lack of motivation and, in the long run, to learning gaps that can further complicate the learning process.

Theories of learning styles state that individuals have different learning preferences, so understanding and applying them in the learning process can significantly increase the efficiency of learning (Kanchon et al., 2024). Knowledge assessment plays a crucial role in improving students' learning experiences. Assessment is an important step for both the formative improvement of the teacher's teaching process and the personalization of the individual student's learning process, depending on the knowledge that students already possess (Riley-Lepo et al., 2024). Traditionally, education researchers distinguish between formative and summative approaches to assessment (Vittorini et al., 2021); however, more recent research also indicates the need to blend these approaches (see, e.g., Svensäter & Rohlin, 2023). Additionally, recent advancements in the field of artificial intelligence have resulted in the proliferation of myriad smart system aids (Owoseni et al., 2024). Despite the emergence of various new technological solutions, traditional methods remain and are often used in assessing different tasks, for example, exams or standardized tests. Traditional tests often face limitations in assessing higher-order thinking competencies (Brown, 2022). Interdisciplinary assessment is usually associated with the concept of STEAM (Science, Technology, Engineering, Art, and Mathematics). In STEAM disciplines, students' knowledge is tested by integrating interdisciplinary tasks that assess not only theoretical knowledge but also the ability to apply it to solve real-world problems. These assessments often use practical tasks or simulations (Gao et al., 2020). Modern assessment methods increasingly rely on machine learning and data analysis to accurately predict student knowledge and identify areas where support is needed. For example, machine learning (ML) models such as gradient boosting can achieve up to 98% accuracy in assessing student knowledge based on data from tasks they complete (Alruwais & Zakariah, 2023).

The rapid development of artificial intelligence (AI) has also made various AI-based solutions for learning personalization possible. The integration of AI into the teaching and learning process can help improve student outcomes by adapting learning content to the existing knowledge and learning styles of students (Sayed et al., 2023). AI applications for educational purposes often rely on advanced technologies focused on text data analysis, such as large language models (LLMs), natural language processing (NLP) techniques, and ML-based models. These models can solve different tasks, for example, generating personal responses, evaluating the quality of content, summarizing information, and more. Using LLMs, it is possible to provide personalized learning content based on a student's level of knowledge and learning style; however, to ensure quality results, it is necessary to formulate prompts properly, as inaccurately formulated questions can lead to incorrect or insufficient answers. LLMs also sometimes provide information that is not completely accurate, so it is important to perform content quality control and make corrections if necessary (Guizani et al., 2025). Despite these challenges, properly used AI tools can significantly contribute to improving and personalizing the learning process. Therefore, this paper aims to review the existing research literature to explore ways artificial intelligence methods could help personalize student learning content.

The authors highlight essential AI techniques currently applied in education and suggest a practical framework that blends traditional teaching strategies with AI-supported approaches to improve the learning experience.

The paper is organized as follows: Section 2 reviews the related works. Section 3 presents' trends in AI methods for personalized learning. The discussion on trends and challenges of personalized learning is presented in Section 4, followed by the conclusion in Section 5.

2. Related works

To identify the latest trends on personalized learning, a systematic analysis of scientific research was performed using the Google Scholar database. Figure 1 illustrates the methodology used in this analysis.

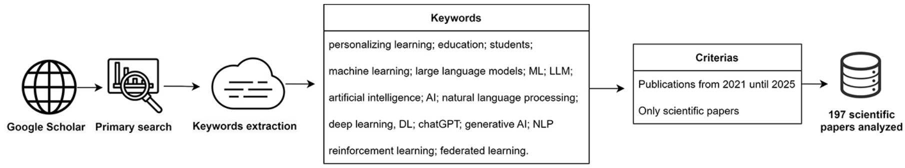

Figure 1. The methodology of systematic scientific literature analysis

The amount of scientific research on personalized learning in Google Scholar is large, exceeding 5 million publications. Therefore, the primary search was conducted using the Web of Science (WoS) database with only three keywords: personalized learning, artificial intelligence, and education. A total of 1,322 publications were found. All discovered publications were used to build a network visualization that shows the relationships between fields and highlights the most frequently used keywords. As can be seen in Figure 2, the most dominant keywords are artificial intelligence, machine learning, education, and ChatGPT. Additionally, smaller topics related to the ones listed above can be distinguished. Thus, the most used keywords were extracted and used in Google Scholar for further literature analysis. The keywords used in the search are presented in Figure 1. Moreover, only papers published between 2021 and 2025 were selected for screening. A total of 197 scientific publications met the selected criteria, and from these, the research team selected the papers that appeared most relevant based on the keywords and abstracts.

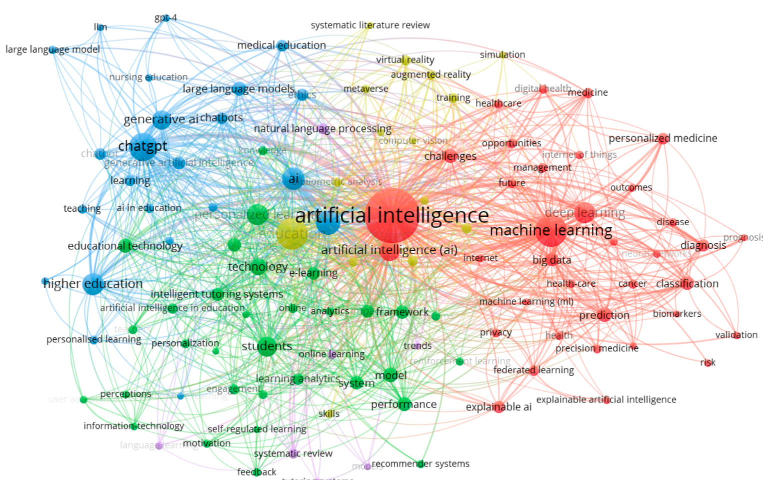

Figure 2. The relationship between the publications of primary search

Personalization of learning content is becoming an increasingly popular topic in the field of education research. With the rapid development of technologies, there is a desire to enable them not only for work or personal needs, but also to improve learning processes. To personalize learning materials as best as possible and help the learner to absorb new learning materials faster and better, numerous studies have been conducted to determine the best methods to achieve this goal. The summary of some valuable research is presented in Table 1.

Table 1. Summary of research related to personalized learning

Author	Aim of research	AI methods used	Data used	Main results
Kanchon et al. (2024)	Identify learning styles and adapt content to learning styles.	Decision tree; random Forest; SVM; logistic regression; CNN, XGBoost; SpaCy; knowledge graph; GPT-3; T5; NER.	Moodle data extracted from the specific courses.	The blending ensemble method with the XGBoost model achieved the best accuracy in determining learning style (97.56%).
Diwan et al. (2023)	To develop an AI-based model for automatically generating learning content.	Zero-shot GPT-2, definition generator.	Wikipedia.	After testing the definition generator model on the NSW topic, the authors generated 1575 definitions and achieved higher ROUGE scores than Zero-shot GPT-2.
Osakwe et al. (2023)	To find the optimal decision sequence that maximizes learning outcomes	LSTM, GA, PPO, RL.	A new dataset was collected by the authors from students' writing and reading tasks.	RL and GA achieved the best performance based on the fitness function results. The LSTM achieved the lower results.
Minn (2022)	To determine how consistent and accurate the cognitive diagnosis and performance prediction of each dominant student model are.	IRT, BKT, PFA, DKT.	Statistical data of secondary school tests, ECPE, TIMSS, ASS-14, ASS-09, Algebra (2005–2006).	The DKT model outperformed the BKT and PFA models on all datasets, while the IRT performed best on most datasets (except ECPE and ASS-14), highlighting its strengths in predictions where task complexity analysis is important.
Kabudi et al. (2021)	To provide insights into AI-based learning systems and their benefits in solving challenges in the learning process.	RL, ML, Decision tree, GA.	Publications from various scientific journals since 2014.	RL methods have shown better results when it comes to optimizing the learning process and personalizing learning based on student behavior. ML methods have been very effective in analyzing student activity and achievement, thus contributing to more effective learning recommendations.

End of Table 1

Author	Aim of research	AI methods used	Data used	Main results
Chang and Sun (2024)	The aim is to delve into not only the practical implementation and deployment of AI, but also its broad impact on modern educational systems and methods.	SRLL	Various publications in WoS from 2000 to 2022.	AI-powered chatbots or intelligent teaching systems promote the development of metacognitive skills and provide personalized feedback, which is very important for independent language learning.
Ezzaim et al. (2024)	To improve learning outcomes in educational settings. This research examines automatic learning style identification in various aspects of education, including methods, models, and implementation.	Decision tree, ANN, naïve Bayes, k-means, fuzzy c-means, k-nearest neighbors, random forest.	Various publications in the WoS and Scopus databases from 2014 to 2022.	decision tree – 25%; ANN 16.7%; naïve Bayes – 12.5%; k-means, k-nearest neighbors, and fuzzy c-means – 6.2%; random forest – 4.2%.

The studies summarized in Table 1 are all related to the application of AI for educational purposes, but each of them is applied in different learning areas. Additionally, factors such as the age of participants, their level of knowledge, and the desired outcomes determine that, in each study, the authors apply different models or use different datasets. Kanchon et al. (2024) used methods commonly applied in the field of artificial intelligence, such as decision tree, random forest, support vector machine (SVM), logistic regression, convolutional neural networks (CNN), and XGBoost. The best results were obtained using the XGBoost algorithm, which achieved 97.56% accuracy.

However, Osakwe et al. (2023), who used long short-term memory (LSTM), genetic algorithm (GA), proximal policy optimization (PPO), and reinforcement learning (RL) methods, obtained the best results using the RL and GA methods. Sein Minn's (2022) study employed less commonly used models, including item response theory (IRT), Bayesian knowledge tracing (BKT), performance factor analysis (PFA), and deep knowledge tracing (DKT), with DKT and IRT models showing superiority over the others. Kabudi et al. (2021) found that the use of RL methods was more effective for optimizing the learning process and personalizing learning based on student behavior, while ML methods were effective for analyzing student performance and achievements. Chang and Sun (2024) used the self-regulated language learning (SRLL) model in their study and concluded that AI-based chatbots and intelligent teaching systems promote the development of metacognitive skills and provide personalized feedback, which is crucial for independent language learning. Ezzaim et al. (2024) also used popular algorithms such as decision tree, artificial neural networks (ANN), naïve Bayes, k-means, k-nearest neighbor, fuzzy c-means, and random forest, with the best results obtained by decision tree and ANN.

Natural language processing (NLP) methods are designed for computers to understand, analyze, and generate human language. These methods cover a variety of tasks, such as speech recognition, text analysis, speech generation, and question answering. Kanchon et al. (2024) used SpaCy, knowledge graph, GPT-3, T5, and named entity recognition (NER) models in their study. Meanwhile, Diwan et al. (2023) used Zero-shot GPT-2 and the definition generator NLP methods, with the definition generator achieving the best results. Although the main research papers selected by the team have been discussed in this section, a number of additional publications have also highlighted another positive aspect of applying AI in education – namely, the possibility of personalizing learning through the use of AI tools.

3. Trends of AI methods for personalized learning

Artificial intelligence methods used to personalize learning content allow the adaptation of content to different student needs, learning styles, and skill levels. Personalization is particularly important for achieving desired results (usually manifested in the curriculum through intended learning outcomes), which may vary depending on the subject matter, the learning material, or the needs of the students. A review of the selected papers showed that the most commonly used methods in the field of personalized learning are large language models (LLMs), natural language processing (NLP) methods, machine learning (ML), and reinforcement learning (RL).

One of the latest technologies with the greatest potential for application in education is large language models. By applying LLMs, teaching content can be tailored to each student, taking into account their strengths, interests, needs, and goals. Unlike traditional education, which follows a one-size-fits-all approach, personalized learning adapts to the student, increasing their engagement and academic performance. Abas et al. (2023) studied the potential use of ChatGPT in personalizing learning in higher education. They highlighted the chatbot's ability to generate natural language responses, where query assistance can easily personalize the student learning experience. The same was emphasized in the study by Wang et al. (2025), in which the authors developed the LearnMate system based on personalized learning guidelines and LLM models. This system focuses on creating teaching plans that take into account students' learning styles and other personal abilities, delivering personalized learning in real time.

Most of the analyzed studies using LLMs also apply additional methods because, to present queries in the correct format, supplementary techniques are needed. For example, it is common to see scientific studies using NLP models such as spaCy and named entity recognition (NER) (Martin & Dominic, 2021). NER models help detect information related to students' habits, preferred working times, learning styles, or certain personal characteristics. In the case of the spaCy model, it is often used to distinguish various morphological aspects of language, especially when comparing information obtained from traditional tests or exams with students' knowledge. Direct comparisons are not always possible, so spaCy and NER models provide significant benefits. Palimkar et al. (2025) used not only spaCy but also machine learning algorithms to improve personalized learning capabilities in e-learning. Similarly, in Kanchon's et al. (2024) study, the highest accuracy in determining the learning style was achieved by the XGBoost algorithm, reaching 97.6%.

Machine learning can be applied not only to personalize learning but also as a tool to distinguish students' original written text from AI-generated text during assessments (Stefanovič et al., 2024). Additionally, various challenges arise when teachers evaluate student work, as they must consider the possibility that students may have used text-generation tools to cheat (Pliuskuvienė et al., 2024). According to Trindade et al. (2025), generative AI is revolutionizing management education by offering innovative teaching and learning methods. They argue that integrating AI into quantitative business disciplines through new learning mechanisms provides significant benefits, including improved data analysis, enhanced decision-making models, and complex simulations of practical experience. Unlike traditional AI, which relies on explicitly programmed rules and algorithms, generative AI uses machine learning methods to independently generate content based on data patterns. The study by Alasadi and Baiz (2023) explores important aspects of AI application in education to advance educational goals. Their findings show that integrating AI into education and research opens new opportunities to transform learning, teaching, and research processes. However, it is crucial to balance the power of AI with addressing associated challenges, ensuring that its benefits are accessible to all while mitigating risks.

NLP is used to create interactive learning tools and tailor content to the learner's language comprehension level. NLP methods assess mood, tone, and linguistic features, allowing models to better handle language nuances such as sarcasm or hidden meanings (Jain et al., 2025). NLP models are widely used in educational processes, such as in foreign language learning apps like Duolingo, which responds to user inputs in real time, or in AI models like GPT-3, which generate texts appropriate to the learner's language level. Shaik et al. (2022) focus on existing NLP methodologies and applications for education, such as mood annotation, entity annotation, text summarization, and topic modeling. They review and analyze trends and challenges in implementing NLP models in education, explaining how context-based challenges – such as sarcasm, domain-specific language, ambiguity, and aspect-based sentiment analysis – are addressed using methods that extract semantic meaning from emoticons and special characters in user reviews. The authors agree that NLP methods play a vital role in analyzing student feedback in text format.

Personalized learning is often used interchangeably with adaptive learning (cf. Peng et al., 2019). Although similar in many respects, adaptive and personalized learning have certain differences. Adaptive learning refers to a technology-driven method where the system automatically adjusts content, pace, or difficulty based on the learner's real-time performance. Personalized learning, while it may include adaptive tools, also involves human decisions (such as teacher input) and can incorporate flexible paths and project-based learning (Taylor et al., 2021).

Adaptive models dynamically adjust learning content and strategies according to students' learning situations and performances. They can adapt the learning content and difficulty in real time to maintain active participation and motivation. By applying adaptive learning algorithms, systems can customize the learning path and content for individual students based on their abilities, interests, and styles (Zheng, 2024). Adaptive models are also used to increase interaction with content. Ipinnaiye and Risquez (2024) conducted a study in which a system using adaptive models created weekly adaptive reading tasks for economics students over six weeks. The study showed that students' learning performance improved.

Reinforcement learning (RL) is a branch of machine learning where an agent learns to make decisions and act in an environment by receiving rewards or punishments. The agent continuously interacts with the environment, optimizes its policy based on feedback, and learns through trial and error which sequences of actions lead to the best outcomes. RL can be very useful in personalizing the learning process, improving student experiences, and helping to achieve better results. According to Fahad Mon et al. (2023), using RL in education enables personalization and adaptation based on student achievements, which can result in increased motivation and engagement.

3. Discussion

Building on the conducted literature review, the authors suggest the following model for blending traditional learning and assessment methods with AI-based learning and assessment methods (see Figure 3).

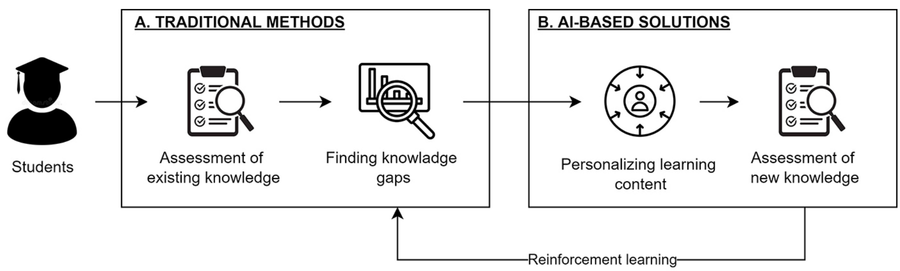

Figure 3. suggested model for blending traditional learning and assessment methods with the AI-based learning and assessment methods

The framework suggested in Figure 3 illustrates a practical blend of conventional and technology-enhanced learning assessment. On the left side, the process begins with traditional methods, such as standardized testing, to establish students' existing knowledge and identify learning gaps (Vittorini et al., 2021; Brown, 2022). While valuable, these tools often overlook the diversity in students' learning styles and motivations (Jørgensen & Brogaard, 2021; El-Sabagh, 2021).

The right side of the figure introduces a shift: once gaps are detected, AI-powered tools step in to personalize the learning experience. Using methods such as large language models, natural language processing (e.g., SpaCy, NER), and reinforcement learning, the system adapts content to meet each learner's needs (Kanchon et al., 2024; Martin & Dominic, 2021). What emerges is a feedback-driven cycle – students engage with tailored content, are reassessed, and the system adjusts accordingly (Osakwe et al., 2023; Kabudi et al., 2021). Research supports this layered approach. For instance, adaptive models using XGBoost have demonstrated high accuracy in identifying learning preferences (Kanchon et al., 2024), while reinforcement learning strategies have been shown to improve how educational content is sequenced and delivered (Osakwe et al., 2023). NLP techniques further enhance personalization by interpreting linguistic and behavioral patterns to refine content delivery (Abas et al., 2023; Wang et al., 2025). However, Figure 3 also implies a need for careful implementation. Systems relying on generative models must be designed with prompt accuracy, ethical safeguards, and mechanisms to review content quality (Guizani et al., 2025). If mismanaged, automation risks misguiding rather than supporting learners. Overall, the model presented in Figure 3 reflects a transition from static, one-size-fits-all instruction to a more responsive, student-focused system – one that learns alongside the learner and evolves with their progress.

5. Conclusions

The systematic literature analysis revealed a lack of scientific papers that analyze personalized learning as a distinct field. Therefore, the main aim of this manuscript was to conduct a systematic scientific literature analysis to explore how artificial intelligence-based solutions can be used to personalize learning content for students. Over the past few years, some practical solutions – such as LearnMate – have emerged. This tool focuses on personalizing learning but also has its limitations. One of the biggest challenges for such systems is the need for multimodal solutions, where different methods must be applied to achieve the goal of assisting students. Additionally, it is difficult to create a flexible system that accommodates diverse targets, such as varying student ages, learning subjects, expected outcomes, or learning languages. Although many multilingual solutions have been developed, less popular or more complex languages often require additional steps.

In this paper, the main AI methods identified for improving students' learning experiences in the educational field are described. The most commonly used methods are large language models, natural language processing, machine learning, and reinforcement learning. The analysis of each AI method is presented, along with an overview of their main applications in education. The results of the systematic analysis enabled the proposal of a possible approach for implementing personalized learning by combining traditional and AI methods, which is presented in this paper.

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