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ARTIFICIAL INTELLIGENCE FOR PERSONALIZED LEARNING : A Literature-Based Review of Approaches, Challenges and Future Directions

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Abstract

The traditional classes proceed at the same rate for all the students. Students enter at various levels and are interested in various things, however. AI is supposed to change all that by altering the content of lessons and the difficulty level. Now, they track how far a user has progressed or give him a hint in a chat. Some success in this can be seen from the papers they looked at. Materials should be modified as necessary based on performance and feedback is beneficial at times. Systems can spot when a student is having trouble too. Many people are concerned about privacy. Another aspect that doesn't always get covered is the types of biases in the way that the algorithms work. Scalability and depending too much on the tech come up as well. However, most of the results are derived from tests that are controlled. It's still very much like "lab stuff, classroom stuff. Increase transparency and ensure teachers are kept up to date perhaps. I believe this is significant, but don't know exactly how it would be done.

Keywords: Personalized Learning, Artificial Intelligence, Adaptive Learning, Machine Learning, Learning Analytic, Intelligent Tutoring System, LLM, Recommendation System, Generative AI, Education

I. Introduction

AI is becoming more prominent in Education. It helps computer systems to process information, identify patterns, create content, and suggest appropriate resources. In learning environments the ability to respond to the needs of individual learners can be applied beyond the individual assumption that the needs of all learners in a class can be met in the same way.

Personalized learning customizes instruction, speed and evaluation, and activities for the needs of each student. Students have varying pre-existing knowledge, interests, strengths, and learning rates, and a single learning sequence may not be suitable for all students. AI can play a role in this adaptation in a number of ways: Machine Learning (ML) can detect patterns in student behavior, Learning Analytics can track student progress, Recommendation Systems can suggest materials that are relevant to the learner, Intelligent Tutoring Systems (ITS) can support students step-by-step, and Large Language

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Models (LLMs) can help explain concepts through conversation and create learning materials. These approaches have been explored in recent surveys and technical studies from various angles [1]–[10].

This paper is a review of the past studies on personalized learning with the aid of AI. It synthesizes the results of various methods, analyses them within a set of common criteria and formulates unresolved questions. It primarily makes the following contributions:

- an overview of the AI methods applied to personalisation, ranging from student modelling to generative tutors; A comparative survey matrix of basic and recent studies including methodology, findings and limitations; a discussion about challenges to privacy, bias, explainability, scalability and Human-HAI collaboration; and An overview of research gaps and future directions for secure, explainable and human-centric AI in the education sector.

The rest of the paper is organized as follows. Section II describes the process of literature search and literature review. The background for personalized learning is introduced in Section III. Finally, the main Artificial Intelligence techniques are described in Section IV and the selected studies are compared in Section V. Ethical and Practical Challenges are discussed in Section VI, while Evaluation is described in Section VII and gaps in research and future directions are examined in Section VIII. The paper ends with a conclusion in section IX.

II. Review Methodology

A. Sources and Search

The relevant research articles, reviews and surveys were collected from IEEE Xplore, ACM Digital Library, Scopus, SpringerLink, ScienceDirect and Google Scholar. Emphasis was placed on more recent publications as AI in education is rapidly evolving and AI specifically generative AI. Where they were relevant to the present study and also gave an important background to the field, earlier studies were also included. These include the one-to-one tutoring system developed by Bloom [11], a comparison between the interaction of humans and computers in tutoring developed by VanLehn [12] and the knowledge-tracing model developed by Corbett and Anderson [13].

A screening and comparison framework is provided. The papers were vetted to find those that were most relevant to AI-supported personalized learning. All selected works were then analyzed based on the following categories: AI technique, data type, learning context, evaluation approach, key findings, and limitations reported. A common framework facilitates comparison of studies, even though the methods and contexts in which they are conducted may be different. A comparison of the results of this test is presented in the survey matrix in Section V.

B. Scope and Limitations of the Review

This study is a review of literature, it doesn't develop It does not collect student data, and it cannot be used to either train a new model or collect data. A detailed mathematical derivation of single algorithms and It is not intended to make comparisons with commercial products. The review is not a formal systematic review, so the studies reported here cannot be considered for the purpose of this review a systematic review. The list of discussed should be considered a representative sample. Not comprehensive coverage of all research in this field.

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III. AI Techniques for Personalized Learning

Most AI-based personalized learning systems have a similar overall structure as illustrated in Fig. 1. Student model is populated with the data collected from the learner. The model is used by the AI engine to select or create personalized responses, the learner reacts to the selected response, and the learner's response is fed to the AI engine for the next round. This loop is surrounded by teacher oversight and privacy and fairness checks.

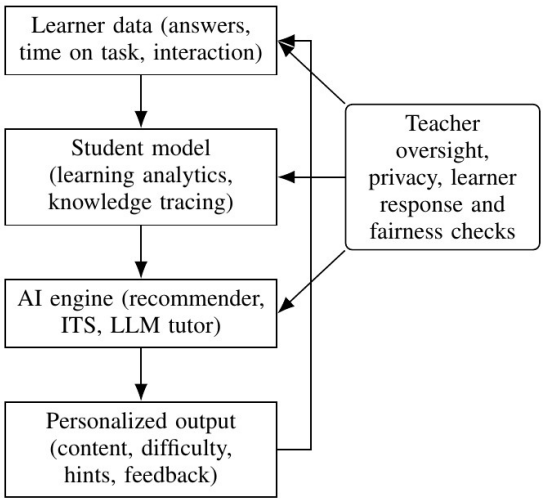


Fig. 1. General structure of an AI-based personalized learning system.

A. Learning Analytics and Student Modeling

Learning analytics involves collecting and analyzing learning data and the learning environment of the students to gain a better understanding and improve the learning process. For the smart education, Wu et al. [3] talked about the personalized learning in the aspects of student and resources recommendations. If there is a useful learner model in the system, they say that the recommendations would be better – but that would require a lot of data. Khosravi et al. [8] explain that AI-powered analytics can be used to forecast student performance and pinpoint students who require further assistance. They also promote the need for protecting student information.

B. Knowledge Tracing

One of the most important techniques for estimation of what the student has learnt is Knowledge Tracing. Instead, Corbett and Anderson [13] suggested a probabilistic approach which bases the probability of knowing a skill on the learner's previous answers. Later, Piech, et al. [14] added Deep Knowledge Tracing, a Recurrent Neural Networks model of sequences of learning activities. They demonstrated that their model was more predictive than previous models for predicting student performance on benchmark datasets. They can be used as a basis to select a next question (or hint or topic) for a system. However, in the general case, deep models are less interpretable than the simpler probabilistic models.

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Algorithmic Workflow and Core Models Typically, a custom learning system will use an iterative algorithm, rather than one AI algorithm. It first gathers activities of the learner, makes an initial guess at what he/she already knows, presents an appropriate learning material, and then adjusting its initial guess on the learner's response. This is outlined below.

Consent and data minimisation guidelines are followed, and answers and attempted answers, response time, topics completed, and interactions with resources are recorded. Develop or study a student model (e.g., Bayesian Knowledge Tracing (BKT) or Deep Knowledge Tracing (DKT)).

1) Identify learning need: make an estimate of mastery compared to the expected mastery level for this learning area and identify which skills may need practising. *Select the following activity:* Prioritize the available lessons, questions or videos according to the learner's knowledge gap, preference and learning goals. *Provide support and update:* give selected activity, hint or explanation; repeat using learner's next response to update the model.

1) Bayesian Knowledge Tracing: Bayesian Knowledge Tracing (BKT) models whether a learner has mastered a skill as a hidden state and updates the estimated probability when a learner answers a question. Let $P(L_t)$ be the probability that the skill is mastered before the response at time t, $P(T)$ the probability of learning after an attempt, $P(G)$ the probability of guessing correctly without mastery, and $P(S)$ the probability of making a mistake despite mastery. For a correct response, the posterior mastery probability can be written as

$$P(L_t|C_t) = \frac{P(L_t)(1-P(S))}{P(L_t)(1-P(S)) + (1-P(L_t))P(G)}. \quad (1)$$

After the response, the model accounts for the possibility that the learner has learned the skill during the attempt:

$$P(L_{t+1}) = P(L_t|C_t) + (1-P(L_t|C_t))P(T). \quad (2)$$

Here, C_t denotes a correct response; an incorrect response uses the corresponding likelihood based on the slip and guess parameters. In practice, the estimated mastery probability can help decide whether to provide another practice question, revisit an explanation, or advance to a new topic. BKT is relatively interpretable, although its assumptions may simplify real learning behaviour [13].

2) Deep Knowledge Tracing: Deep Knowledge Tracing is a recurrent neural network which processes a sequence of learner responses. Every interaction is recorded as an input, including the skill that was attempted and if the answer was correct or not. The network keeps a "memory" of previous interactions, and leverages this to make predictions about future skills. Historical interaction sequences are used to learn the parameters of the model. DKT can represent more complex patterns than a simple probabilistic model, but it can require more training data and may not be as easy to explain [14].

3) Resource Ranking and Recommendation: Once the student model has generated an estimate of the learner's needs, a recommender can rank the candidate resources. The simple illustrative scoring function is

$$R(u,r) = w_m\, M(u,r) + w_g\, G(u,r) + w_p\, P(u,r), \quad (3)$$

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where $R(u,r)$ is the score of the resource r when recommended to learner u, $M(u,r)$ is relevance to current mastery level of learner u, $G(u,r)$ is a gap (such as score), and $P(u,r)$ is preference or format suitability. The weights w_m, w_g, w_p specify the importance of each factor. This score may be used to prioritize resources and select activity. This equation does not imply that all the systems surveyed have the same equation, but rather represents a general approach to ranking. Some advanced systems might involve collaborative filtering or content-based techniques, or deep-learning recommenders [3, 9].

4) Role of Intelligent Tutors and Large Language Models: The Intelligent Tutoring System can be designed to include A Domain model, Student model, and Tutoring rules. For example, when a student mistakenly inputs the answer a few times, the system might provide a hint, break down a problem into smaller steps, or recommend learning some prerequisites. An LLM-based tutor can offer a natural language explanation or practice question, given the context of the learner's topic and estimated level. When generating content however, there should be a checking for its correctness and its age appropriateness and important decisions about teaching should be left to the teacher [10] [15].

The above workflow is a hybrid of literature studied and is not an algorithm newly implemented or tested. This paper is to be based on literature, and does not assert training results or measured performance of the described workflow.

C. Recommendation Systems

Recommendation systems can be employed to recommend to a learner resources such as video lectures, exercises, reading or assignments relevant to the learner's needs. The deep learning-based recommendation methods have been investigated by Chen et al. [9] and it was found that they can enhance the selection of relevant materials. There is one negative point, however: these techniques could require a considerable amount of computing power. Furthermore, Wu et al. [3] point to modeling-recommendations relationship: The more a system can be informed about a learner's knowledge and needs, the more useful the suggestions made by the system can be.

D. Intelligent Tutoring Systems

Intelligent Tutoring Systems (ITS) give students hints, explanations and feedback depending on student's progress. There are reports from Ahmad et al. [10] that these systems can adapt to the type of assistance that they provide, but that scaling up and dealing with various learning contexts are challenging. In the same way, VanLehn [12] demonstrated that a well-structured subject area can be as effective with ITS as a human tutor. This means this type of system is likely to be appropriate where concepts and steps in problem solving are easily defined.

Subsection: Generative AI and Large Language Models Personalized learning has been infused with a conversational twist through the use of Generative AI and Large Language Models (LLMs). They can teach subjects in different ways and provide you with practice questions, answer your questions, and provide feedback as you go. Some of the possibilities and barriers of these tools have been discussed by Kasneci et al. [15]. Their research suggests that LLM may be able to help develop customized content for every student and even reduce some of the repetitive work for teachers.

However, LLM's can be wrong or might be biased. Other issues include reliance on AI, copyright and managing student information. Students and teachers should check AI-generated text, rather than

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assuming it is accurate. Thus, LLM tutoring must go hand in hand with the proper teacher supervision, and should be given in combination with, and not instead of, human supervision.

A comparison of the literature from this study is below. Table I summarizes all the studies included in this paper, showing the methods used, the main results, and limitations of the studies. The works chosen can be divided into the following three broad groups for comparison.

The first ones are review papers and conceptual frameworks [1]-[2] [4]-[7] which discuss the broader impact of AI's applications in education. The second group relates to technical issues concerning learning analytics, recommendation systems and intelligent tutoring [3] [8] - [10] [14]. The third group consists of foundational and critical studies [11]– [13] [15] [16] that provide explanations for the development of personalized learning and point out concerns associated with its implementation.

Table I: Summary of Surveyed Studies

Study	Methodology and key finding	Limitation
Merino-Campos [1]	Systematic review; AI improves personalization and engagement	Privacy concerns
Laak and Aru [2]	Human–AI framework; collaboration supports personalization	Limited learner autonomy
Wu et al. [3]	Learning analytics and student modeling; better recommendations	Needs large datasets
Peng and Li [4]	Systematic review; AI enhances personalization in higher education	Infrastructure and implementation challenges
Hariyanto et al. [5]	Review of adaptive learning; customized learning paths	Implementation and scalability
Holmes et al. [6]	AI in education framework; supports assessment and feedback	Ethical and transparency concerns
Zawacki-Richter et al. [7]	Systematic review; supports teaching and learning	Limited practical validation
Khosravi et al. [8]	Learning analytics; predicts student performance and needs	Student data privacy
Chen et al. [9]	Deep learning recommendation of learning resources	High computational requirements
Ahmad et al. [10]	Intelligent tutoring; adaptive feedback and support	Scalability and contextual understanding

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Study	Methodology and key finding	Limitation
Bloom [11]	Experiment comparing one-to-one tutoring with classroom teaching; about two standard deviations gain	Tutoring is not scalable
VanLehn [12]	Review of human and computer tutoring; ITS can be nearly as effective	Mostly structured subjects
Corbett and Anderson [13]	Probabilistic knowledge tracing model	Limitation not stated in the summary used here
Piech et al. [14]	Deep Knowledge Tracing using RNNs; improved performance prediction	Limited interpretability
Kasneci et al. [15]	Review of LLMs in education; content, explanation and feedback	Bias, wrong answers and over-reliance
Baker and Hawn [16]	Review of bias in education; unequal performance across groups	Bias measurement is still developing

Based on this comparison, I have some thoughts. First, the majority of research shows that it is good to be personalized, with benefits such as more relevant recommendations, more feedback, more engagement or more learning support. Second, many of the same shortcomings are found throughout the literature. They include privacy and ethical issues [1, 6, 8], requirement for large computing resources and large datasets [3, 9] and practical implementation and scalability issues [4, 5, 10]. Thirdly, the issues are not technical. The learner independence and possibly overdependence on AI are also factors [2, 15]. Good utilization of a system is not the only important aspect of successful personalized learning, but also how teachers will utilize a system in the classroom and how they will support the utilization of that system.

A contrast between technical performance and evidence of classroom practices is also indicated in the comparison. Nevertheless, the accuracy of prediction or recommendation quality was studied in various environments, but not the long-term learning or learner motivation aspects, nor the effects on teachers' workload. Likewise, the studies that were examined by Zawacki-Richter et al. [7] were not sufficiently practically validated. The knowledge gained in one course at one institution/country does not necessarily have to be transferred to another course at another institution or to another country.

IV. Challenges and Ethical Concerns

The subject of data protection and privacy is examined. Data protection and privacy are studied. Personalized learning systems typically maintain logs of student response, time on task, interactions with the system, and more. Voice or video may be used in some systems, too. This information can provide clues to learning habits and personal characteristics, so it is important to safeguard student privacy.

Data should only be gathered by institutions to which it is relevant, informed consent should be obtained, and student information should be kept in a secure manner. Wherever an AI tool is accessing data from

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an external cloud service, they should also review who has access to that data and where it's stored. Among the studies reviewed here [1] and [8] privacy has been identified as a concern. It should therefore be considered an essential component of personalized learning and not something that is only an add-on.

The issue of algorithmic bias and fairness is also a key concern. There's also a concern about algorithmic bias and fairness. AI systems might not be equally effective in supporting all sets of students. Baker and Hawn's review of algorithmic bias in education [16] identified that algorithmic models can yield various outcomes for different groups, including racial, gender and socioeconomic classification.

Prediction networks based on these models can perpetuate inequalities if they are used to make recommendations for accessing resources and determining students in need of assistance. A less accurate model, for instance, for a student population that is underrepresented may not account for the learning needs of that sub-population. Fairness checks, transparency in reporting and student group comparisons are meaningful actions towards equitable systems.

A. Explainability and Transparency

The student and teacher should be able to comprehend the rationale behind the recommendation of an AI system, particularly when it influences learning activity or assessment. If a system provides advice without stating how, then it is more difficult to assess or question the advice.

Decision making for deep knowledge tracing is more difficult to explain than past methods [13, 14] and more accurate in predicting student performance. Ethical and transparency issues in educational context with the use of AI are also explored by Holmes et al. [6]. The issues indicate the necessity of student models to explain why a topic/ exercise/ resource has been recommended. These reasons would assist the teacher in determining if a suggestion is appropriate for the student.

The scalability and resource requirements are considered. Scalability and resource requirements are taken into account. While AI can help with personalized instruction, there are cases where it is not so easy to implement it on large-scale institutions. Other methods require a considerable amount of information, computational power, and a reliable infrastructure [3, 9]. Implementation and scalability are also listed as current challenges by Peng and Li [4] and Hariyanto et al. [5].

However, these requirements can be challenging for institutions with constrained budgets or technical resources. It can be difficult to run a system that works well when it's scaled down in a small trial scenario, let alone thousands of students. Therefore, the cost, ease of deployment and maintenance should also be taken into consideration by developers in addition to model performance.

1) Over-Reliance and the part of teachers: A potential issue of LLM-based learning tools is that students may over-rely on students' answers [15]. Without reviewing the AI-generated responses, this can restrict the space for developing independent thinking and solving problems.

Laak and Aru [2] present a Human–AI framework that focuses on collaboration between educators and AI. AI might generate practice questions, monitor progress, or provide initial explanations, leaving teachers responsible for guidance, motivation, and important decisions. This equilibrium would enable schools to reap the benefits of AI without compromising the autonomy of learners and the teacher's centrality.

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Evaluate the effectiveness of Personalized Learning Systems. The assessment of a personalized learning system is more than a technical accuracy. The model can be analyzed to see if it predicts student performance or the recommendation system can be analyzed to see if it is selecting the most appropriate learning resources. These measures serve to show if the technical tasks of the system are carried out as expected.

Technical results, however, will not reveal if students are learning incrementally. Additionally, learning gains, engagement, course completion, and student satisfaction should be taken into account. The impact of the system on the teacher, such as its ability to decrease routine tasks and/or deliver information that supports the decision making process for teaching, is also important to consider.

A separate check should also be made to see whether the system is equitable to various groups of children [16]. A good overall performance may disguise a lack of performance for individual learners. A general overview of the group level results can provide insights into these differences.

The findings of this review indicate that more often study is reported rather than educational outcomes, with regard to technical measures. There is a need for further studies measuring both, having a longer timeframe of follow-up students and a test of systems in different courses and institutions. This would make it easier to identify if early gains are sustained in the long term and result in meaningful learning gains.

V. Research Gaps and Future Directions

A. Research Gaps

Based on the reviewed studies, it is recommended that more work be done on the following issues:

There is limited evidence on long-term learning outcomes, student motivation and the effect of AI tools on teachers' workloads. Many of the studies focus on one problem, institution or country so it is hard to know if their findings are transferable to other educational contexts. Large Language Models' deep learning models and recommendations are often hard to interpret, making it hard for teachers and students to understand why they made their decisions. Bias identification and mitigation in education AI models are still under research [16]. However, the use of AI tools in real classroom environments is still limited [7]. There is a need for more focus on learner autonomy and safe and critical use of generative AI [2, 15].

B. Future Directions

There are a number of courses of action to pursue with regard to improving personalized learning systems. A priority is to "Create student models" that will explain why a topic or the resource is recommended. This would provide teachers with a better understanding of the system's reasoning, and help them to decide whether a recommendation is suitable for the learner.

A second trajectory is to integrate multimodal information in multimodal systems, namely text, speech and interaction information. Students should not be judged based on one type of information alone; using more than one type of information may help give a more complete picture of student progress. Emotion-aware tutoring could also be investigated to respond to potential frustration or decreasing interest. Both

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of the approaches have to be tested carefully to determine their reliability and usefulness in actual classrooms.

Multilingual support will be relevant in India where there are numerous languages students use. AI tools to explain concepts and give study materials in regional languages may be helpful to learners who study better in a language other than English. Virtual tutors could also be accompanied by Virtual Reality (VR) or Augmented Reality (AR) that can make some learning activities more interactive. It could be helpful in courses where it's important to demonstrate or simulate things visually. Their value should, however, be determined in the context of what evidence of learning is achieved, not in the context of whether the technology is new or novel.

Future systems development should focus on understandable, fair, accessible, and teacher-friendly systems. Pilot testing in various institutions and with various groups of students will test their ability to provide meaningful and sustainable benefit.

VI. Conclusion

Based on the analysis, the current paper reviewed the use of Artificial Intelligence for Personalized Learning (PAI) focusing on adaptive learning, learning analytics, student modeling, recommendation systems, Intelligent Tutoring Systems, and Large Language Models. The studies reviewed show that a paradigm change has occurred from traditional digital learning environments to digital platforms that are capable of adapting content, levels, explanations, and feedback to the individual student.

Past research into one-to-one tutoring shows the benefits of personal attention, while recent research examines how AI could enable limited types of one-to-one tutoring to more learners. AI tools can estimate progress by using learning analytics and knowledge tracing, and offer guidance through a problem with intelligent tutors and point students toward relevant resources with a recommendation system. Generative AI enhances with conversational explanations and a These opportunities come with important challenges. Student privacy, algorithmic bias, the ability to explain AI decisions, computing costs, and excessive reliance on AI all need attention. In addition, the limited evidence on long-term classroom outcomes means that better technical performance should not automatically be taken as proof of better learning. Further research should focus on systems that are explainable, fair, multilingual, and built to complement teachers' work. Studies conducted in real classrooms are needed to understand their longer-term effects on both learners and educators. Through proper protection mechanisms as well as human supervision, AI can facilitate the adaptation, accessibility, and personalization of education.

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