DESIGNING ARTIFICIAL INTELLIGENCE-BASED PERSONALIZED LEARNING IN HIGHER EDUCATION: A CONCEPTUAL MODEL AND PEDAGOGICAL-ETHICAL CONDITIONS

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Abstract. This article examines the theoretical and methodological foundations for designing artificial intelligence (AI)-based personalized learning in higher education. The study does not report empirical findings; rather, it presents a conceptual-analytical review grounded in peer-reviewed research and official documents issued by UNESCO and the OECD. The analysis systematizes the potential of AI for learner modelling, learning-outcome prediction, adaptive content selection, individualized feedback, and teacher decision support. Based on the synthesis, a six-component conceptual model is proposed, comprising data acquisition, a dynamic learner profile, a pedagogical decision mechanism, adaptive content, continuous feedback, and ethical-pedagogical governance. The model is founded on a balance between algorithmic automation and meaningful human oversight. The article also discusses data privacy, algorithmic bias, explainability, academic integrity, digital inequality, and the risks of excessive dependence on AI. It argues that AI should be implemented not as a substitute for teachers, but as a tool that supports evidence-informed pedagogical judgement. The proposed model may provide a theoretical foundation for the design of adaptive courses, intelligent tutoring systems, and learning analytics platforms in higher education.

Keywords: artificial intelligence; personalized learning; adaptive learning; learning analytics; learner model; explainable artificial intelligence; academic integrity.

1. Introduction

The expansion of digital learning ecosystems has made the limitations of conventional higher education increasingly visible. Traditional instructional models commonly provide the same content, pace, assignments, and assessment instruments to all students. However, students differ in prior knowledge, cognitive strategies, learning pace, motivation, digital competence, and access to learning resources. Consequently, a uniform instructional pathway may be excessively demanding for some learners and insufficiently challenging for others.

Personalized learning refers to the adaptation of learning objectives, content, tasks, pace, or feedback to a learner's needs, current knowledge state, and developmental trajectory. Although this approach is rooted in long-standing principles of individualized education, artificial intelligence and learning analytics substantially increase its scalability in large cohorts. Research on AI in higher education has concentrated particularly on learner profiling and outcome prediction, automated assessment, intelligent tutoring, adaptive systems, and personalization [1, 2].

Nevertheless, the presence of AI does not in itself guarantee educational effectiveness. A technically accurate model may still serve an inappropriate pedagogical objective, rely on insufficient or biased data, or generate decisions that are not intelligible to students and teachers. Recent reviews indicate that technological solutions are not consistently integrated with pedagogical theory, stakeholder participation, and ethical governance [3, 4]. The central question is therefore not simply whether AI should be used, but under which pedagogical architecture and accountability mechanisms it should operate.

The purpose of this article is to systematize the structural mechanisms of AI-based personalized learning in higher education and to develop a conceptual model that integrates pedagogical and ethical requirements. To achieve this purpose, the article clarifies the concept of personalization, analyzes the principal educational functions of AI, proposes a six-component model, identifies implementation risks, and formulates practical recommendations for higher education institutions.

2. Research Methodology

The study employs a theoretical and conceptual review methodology. Because no empirical experiment was conducted, the article deliberately avoids unverified claims such as “effectiveness was proven” or “learning outcomes increased.” The analysis draws on peer-reviewed studies and institutional documents addressing artificial intelligence in higher education, personalized and adaptive learning, learning analytics, explainable AI, academic integrity, and AI competencies.

The analysis was conducted in three stages. First, the educational functions of AI and the elements subject to personalization were extracted from the selected sources. Second, these functions were organized into the sequence data–model–decision–pedagogical intervention–feedback–governance. Third, the identified components were synthesized into a conceptual model, after which the model’s pedagogical opportunities, ethical risks, and institutional requirements were examined.

Sources were selected on the basis of the availability of a DOI or official publication record, the academic or institutional standing of the publisher, transparency of the methodology, and relevance to the purpose of the article. The review is not presented as a comprehensive PRISMA-based systematic review; it is a purposive conceptual synthesis intended to develop a theoretically coherent model. This limitation is explicitly acknowledged in the interpretation of the findings.

3. Theoretical Foundations of Personalized Learning

3.1. Conceptual Scope of Personalization

Although personalization, individualization, and differentiation are closely related, they are not synonymous. In differentiated instruction, students are grouped according to selected characteristics and different tasks are assigned to each group. Individualization primarily allows learners to work at their own pace. Personalization, by contrast, dynamically modifies the learning pathway in response to the learner's current state, goals, choices, and performance. A systematic review of personalized learning in higher education found that knowledge level and individual characteristics are among the most frequently used criteria, while recommendation is one of the core functions of personalized systems [5].

The defining feature of AI-based personalization is continuity. Initial diagnostics provide a preliminary profile, but this profile is revised throughout the learning process. Test errors, task-completion time, the frequency of requesting assistance, repeated engagement with specific topics, and teacher observations may all modify the system's representation of the learner. Personalization should therefore be understood as a cyclical process rather than a one-time classification.

3.2. Principal Pedagogical Functions of Artificial Intelligence

The literature identifies several interrelated educational functions of AI. The first is diagnosis and prediction: machine-learning algorithms are used to estimate knowledge states, identify students who may experience difficulty, and predict the probability of course completion. The second is adaptive recommendation, through which a system selects topics, tasks, examples, or levels of support according to the learner profile. The third is automated assessment and feedback. The fourth is intelligent dialogue and generative assistance. The fifth is the provision of analytical dashboards and decision support for teachers [6, 7].

These functions should not operate as isolated technical services, but as parts of a coherent pedagogical cycle. For example, a prediction model may categorize a student as "at risk," yet such a prediction has limited educational value unless it leads to an appropriate instructional response. Likewise, a generative model may produce immediate feedback, but that feedback may be pedagogically weak if it supplies a complete answer without encouraging reasoning or reflection.

The pedagogical value of AI should therefore be assessed not by the volume of automated responses it generates, but by the extent to which it supports meaningful learner activity. Chen et al. draw attention to the gap between practical AI applications and educational theory [8]. Accordingly, the purpose of an algorithm should be to guide learners toward the next stage of reasoning, help them recognize misconceptions, and support independent decision-making rather than merely deliver ready-made answers.

4. A Conceptual Model of AI-Based Personalized Learning

The theoretical synthesis supports a six-component conceptual model for higher education. Its logic is cyclical: learner activity produces data; these data are transformed into a dynamic profile; the profile informs a pedagogical decision; the decision is implemented through adaptive content or support; the resulting learner response provides new evidence; and the entire process is governed by ethical and pedagogical principles. Human oversight is not an external addition to the model, but a constitutive element of every stage.

Table 1. Components of the conceptual model of AI-based personalized learning

No.	Component	Primary function	Pedagogical requirement
1	Data acquisition	Records diagnostic results, assignments, completion time, error patterns, activity, and teacher observations.	Collect only data required for a defined pedagogical purpose; ensure informed consent, security, and proportionality.
2	Dynamic learner profile	Models knowledge state, misconceptions, learning pace, engagement, and need for support over time.	Do not treat the profile as a fixed label; represent uncertainty and allow correction of inaccurate data.
3	Pedagogical decision mechanism	Recommends the next topic, task, resource, intervention, or level of assistance.	Decision criteria must be intelligible, pedagogically justified, and open to teacher modification.
4	Adaptive content	Adjusts content, difficulty, format, sequence, pace, and the amount of scaffolding.	Adaptation must remain aligned with intended learning outcomes and disciplinary methodology.
5	Continuous feedback	Provides timely explanations, hints, error-specific guidance, and recommendations for the next step.	Feedback should promote reflection and gradually reduce support rather than replace learner effort.

No.	Component	Primary function	Pedagogical requirement
6	Ethical-pedagogical governance	Regulates data use, transparency, human oversight, accountability, auditing, and appeal mechanisms.	High-stakes decisions must not be delegated exclusively to an algorithm; human agency must be preserved.

4.1. Data and the Dynamic Learner Profile

The first requirement of a personalized system is reliable and educationally meaningful data. The number of platform logins or the time spent on a screen does not, by itself, provide a valid representation of learning. Test results, the quality of practical work, types of error, use of assistance, teacher observations, and the learner's self-assessment should therefore be interpreted together. Data quality is a pedagogical issue as well as a technical one: an inaccurate indicator can lead to an inappropriate intervention.

The state of learner i at time t may be represented conditionally by the following vector:

$$P_i(t) = \{K_i(t), S_i(t), E_i(t), A_i(t), H_i(t)\}$$

where $K_i(t)$ denotes the learner's knowledge and skill state; $S_i(t)$, learning pace; $E_i(t)$, the profile of errors and misconceptions; $A_i(t)$, learning activity; and $H_i(t)$, the need for system or teacher support. These indicators should not be interpreted as deterministic truths. They are estimates derived from observations and should include uncertainty, opportunities for correction, and teacher judgement.

4.2. Pedagogical Decision-Making and Adaptive Content

The pedagogical decision mechanism is the link between the learner profile and the intended learning outcomes. An algorithm should not be limited to the question "What does the student prefer?" It should address the more educationally significant question: "What learning activity is currently required for this student to achieve the intended competence?" Recommendations must therefore reflect curriculum goals, prerequisite relations, disciplinary logic, and teacher-defined methodological rules.

The selection of the most appropriate learning resource may be represented conditionally as the following optimization problem:

$$r^* = \arg\max U(r \mid P_i(t), G, C, T)$$

where r^* is the recommended resource or activity; $P_i(t)$ is the learner's current profile; G represents the learning goals; C denotes organizational and technical constraints; T represents teacher-defined methodological rules; and U is the expected pedagogical utility function. The expression highlights a central principle of the model: algorithmic recommendation must be subordinated to learning goals and pedagogical constraints.

Adaptive content may modify the level of difficulty, type of example, media format, sequence of activities, amount of support, and pace of progression. In a programming course, for instance, a learner who demonstrates adequate algorithmic reasoning but frequently makes syntactic errors may receive debugging and code-correction exercises. A learner who struggles with algorithmic structure may instead be provided with flowcharts, worked examples, and stepwise decomposition tasks. Thus, the same final competency may be pursued through different instructional pathways.

4.3. Feedback and Explainability

Effective feedback should not be reduced to announcing whether an answer is correct or incorrect. It should indicate the likely source of the error, provide a question or hint that guides the learner toward a solution, and identify an appropriate next step. The level of automated support should also be adaptive: an initial prompt may be followed by partial guidance and, only when necessary, a more detailed explanation. This graduated approach preserves the learner's responsibility for completing the task.

Explainable artificial intelligence is particularly important in education because algorithmic decisions can shape a learner's pathway. Khosravi et al. emphasize that explanation in educational contexts is not merely a technical feature of a model, but a process of communicating relevant information to different stakeholders, including students, teachers, and administrators [9]. A student should be informed which errors or learning indicators led to a recommendation, while a teacher should be able to inspect the model's confidence and the factors influencing its output.

5. Discussion: Opportunities and Limitations

5.1. Pedagogical Opportunities

The first advantage of the proposed model is its potential to redirect the teacher's attention from routine data collection toward pedagogical interpretation and targeted support. In a large class, manually identifying the topics and misconceptions that cause difficulty for each learner is demanding. Learning analytics can reveal recurring error patterns and changes in engagement, enabling the teacher to prioritize students who need timely assistance.

A second advantage is the timeliness and differentiation of feedback. When the interval between an error and an explanation is reduced, learners are more able to revisit the reasoning that produced the error. Third, the model can provide enrichment activities for advanced learners and structured scaffolding for those who require additional support, without permanently categorizing either group.

The OECD notes that adaptive tools may strengthen the monitoring of learning progress and individualized support, provided that they are governed by clear pedagogical purposes and teacher oversight [10]. Its subsequent analysis of generative AI similarly concludes that educational value depends on well-designed learning activities, explicit instructional principles, and active teacher involvement rather than on the technology alone [11].

5.2. Ethical and Cognitive Risks

The data collected for personalization may generate a detailed representation of a student's academic performance, errors, and behaviour. Data minimization, informed consent, restricted access, defined retention periods, and the reduction of identifiable information are therefore essential. UNESCO identifies the protection of human rights, personal data, and age-appropriate use as central principles for the adoption of generative AI in education [12].

Algorithmic bias is another serious risk. Low platform activity does not necessarily indicate low motivation; it may result from limited internet connectivity, restricted device access, language barriers, employment, or family responsibilities. If a model learns historical inequalities, it may systematically underestimate the potential of particular groups. Consequently, performance and error rates should be examined across relevant learner groups, and algorithmic recommendations should be regularly audited.

Excessive use of generative assistance may also weaken independent problem-solving and critical reflection. A systematic review by Zhai et al. discusses the risks that over-reliance on AI dialogue systems may pose to decision-making, analytical thinking, and critical thinking [13]. Personalization should therefore be based on the principle of organizing the next step that the learner can perform independently, rather than completing the task on the learner's behalf.

Academic integrity similarly requires a redesign of assessment. In contexts where complete text or code can be generated rapidly, the final product alone is not a sufficiently reliable indicator of learning. Problem selection, comparison of alternative solutions, documentation of the working process, source verification, oral defence, and reflective commentary should become integral to assessment. Chan proposes that institutional AI policy in higher education should address pedagogical, governance, and operational dimensions as an interconnected ecosystem [14].

5.3. Teacher and Learner Agency

Human actors must remain the principal pedagogical agents in AI-supported systems. Teachers define learning objectives, establish recommendation rules, interpret algorithmic outputs in context, and override them when necessary. Learners, in turn, should not be passive recipients of recommendations; they should be able to understand, question, and, where appropriate, reject or correct the system's representation of their learning needs.

Research on human-centred learning analytics indicates that end users, particularly students, are not consistently involved in the design of educational AI systems [15]. This can result in tools that function technically but fail to reflect users' actual needs and values. Students and teachers should therefore participate in prototype testing, the selection of explanation formats, the design of notifications, and the determination of appropriate levels of user control.

UNESCO’s AI competency frameworks for students and teachers emphasize a human-centred mindset, ethics, foundational knowledge of AI, responsible application, and the capacity to create with AI [16, 17]. Procuring an AI tool or connecting it to a learning platform is therefore only the technical dimension of implementation. AI literacy and pedagogical design competence must be developed in parallel.

6. Practical Recommendations for Higher Education Institutions

The following sequence is recommended when implementing the conceptual model in higher education:

1. Define the pedagogical problem before selecting the technology. The institution should specify whether the objective is early identification of difficulty, timely feedback, personalized resource recommendation, or another clearly delimited educational need.

2. Conduct a small-scale pilot. Initial implementation should be limited to one course or module, and evaluation should consider learning outcomes, student experience, teacher workload, and the accuracy and usefulness of recommendations.

3. Apply the principle of minimal and high-quality data. Every data field should be linked to an explicit pedagogical decision; data that do not serve a defined educational purpose should not be collected.

4. Preserve meaningful human oversight. Final grades, disciplinary conclusions, and decisions that restrict educational opportunities must not be delegated exclusively to an algorithm.

5. Establish explanation and appeal mechanisms. Students should be able to understand the basis of a recommendation and challenge inaccurate data or inappropriate conclusions.

6. Assess the learning process, not only the final product. Source verification, justification of decisions, oral defence, version history, and reflection can strengthen academic integrity.

7. Implement algorithmic auditing and continuous monitoring. Recommendation accuracy, unequal error patterns, user complaints, and potentially discriminatory outcomes should be reviewed regularly.

8. Develop AI literacy among teachers and students. Users need to understand the capabilities, limitations, privacy implications, and responsible-use requirements of the system.

The effectiveness of implementation should not be evaluated solely through test scores. A multidimensional evaluation should consider learning progress, independent work, dependence on assistance, critical thinking, course withdrawal, user trust, teacher time, and algorithmic fairness. This broader approach prevents technically measurable indicators from displacing educationally meaningful outcomes.

7. Limitations and Directions for Future Research

This article is conceptual and analytical; the proposed model has not yet been subjected to empirical testing. Accordingly, no definitive claims can be made regarding its effectiveness, transferability across disciplines, or implementation costs. In addition, the sources were selected purposively rather than through an exhaustive database search. The article should therefore be regarded as a theoretically grounded framework that requires validation, not as evidence of causal effectiveness.

Future research should develop and evaluate a software prototype based on the model, test the reliability of the dynamic learner profile, examine the effects of teacher overrides on system performance, and assess algorithmic fairness across different social and educational groups. Experimental and quasi-experimental studies should also compare forms of generative support that promote independent reasoning with forms that may encourage dependence. Mixed-method designs would be particularly valuable because they can combine learning outcomes with student and teacher experiences.

8. Conclusion

Artificial intelligence creates significant opportunities to implement personalized learning at the scale of higher education. It can integrate multiple sources of learner data, model knowledge states dynamically, recommend appropriate tasks and resources, generate timely feedback, and support teacher decision-making. The article has proposed a six-component model that connects these functions within a single pedagogical and ethical cycle.

However, the quality of personalization is not determined by algorithmic complexity alone. It depends on the relevance of the pedagogical objective, the validity and proportionality of the data, the explainability of recommendations, the preservation of learner and teacher agency, and continuous human oversight. These conditions are particularly important when AI outputs influence assessment, access to educational opportunities, or students' perceptions of their own abilities.

AI should therefore be understood not as a replacement for the teacher, but as an analytical partner that can extend professional judgement. Personalized learning becomes educationally responsible only when pedagogical design, ethical governance, AI literacy, and algorithmic auditing are implemented together. The proposed model offers a theoretical foundation for such integration and provides a basis for subsequent empirical validation in higher education settings.

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