ARTIFICIAL INTELLIGENCE IN MODERN PEDAGOGY: A HUMAN-CENTERED FRAMEWORK FOR PERSONALIZED LEARNING AND TEACHING

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Abstract. Artificial intelligence (AI) can support pedagogical differentiation, but the production of individualized content does not by itself constitute personalized education. This conceptual review examines how teachers may integrate generative and predictive AI tools into classroom decision-making while retaining responsibility for learning goals, inclusion, and assessment. A structured thematic synthesis of established educational theory and selected scholarly and intergovernmental publications informs a proposed Human-Centered Personalized Pedagogy (HCPP) framework. The framework organizes implementation around learner diagnosis, co-designed goals, bounded AI scaffolding, dialogic classroom activity, evidence-based feedback, and teacher-led review. It also identifies safeguards addressing inaccurate output, language inequity, data minimization, and dependence on automated assistance. Rather than reporting experimental outcomes, the article supplies a theoretically grounded model and a set of indicators that future studies can evaluate. The analysis argues that meaningful personalization requires changes in instructional interaction and learner agency, not merely a higher volume of AI-generated exercises.

Keywords: artificial intelligence; personalized learning; human-centered pedagogy; differentiated instruction; teacher agency; educational ethics

1. Introduction

Personalized learning is widely invoked as a promise of educational technology, yet personalization can mean very different things. In its narrow form, a system changes the difficulty of a worksheet or recommends the next question. In a stronger pedagogical form, instruction responds to learners' prior knowledge, language backgrounds, interests, misconceptions, and developing capacity for self-direction. Generative AI extends the range of possible adaptations by producing explanations, examples, practice activities, and dialogues quickly. Its flexibility, however, also increases the possibility that an apparently appropriate response is factually wrong or pedagogically unproductive (Kasneci et al., 2023).

A central question is therefore not whether AI can generate individualized materials, but under which instructional conditions individualized support improves opportunities for learning. UNESCO (2023) emphasizes human agency and appropriate safeguards, while UNESCO (2021) places equity and inclusion within educational AI policy. These principles suggest that the teacher's diagnostic and relational work cannot be outsourced to an automated model. This paper develops a teacher-governed implementation framework that connects AI affordances with instructional judgment, learner choice, and accountability.

2. Methodological Approach

The article employs a conceptual integrative review rather than a systematic review or empirical experiment. Sources were purposefully selected for their relevance to three intersecting domains: generative AI in education, human-centered governance of AI, and established principles of pedagogy and self-regulated learning. The corpus includes UNESCO policy guidance and peer-reviewed educational analyses (UNESCO, 2021, 2023; Kasneci et al., 2023; Tlili et al., 2023; Zimmerman, 2002).

The analytical procedure comprised four steps: identifying recurring opportunities and risks; distinguishing automation from pedagogical personalization; translating the themes into an instructional sequence; and deriving observable implementation indicators. The synthesis is interpretive, not a quantitative estimate of effectiveness. No classrooms, teachers, or students were recruited; no original learning-outcome data were collected. The proposed framework is therefore a design proposition requiring subsequent field validation.

3. Results: The Human-Centered Personalized Pedagogy Framework

The synthesis supports six linked design phases. First, the teacher establishes a learning profile using low-stakes diagnostic tasks, student explanations, and contextual information learners voluntarily provide. AI may help draft diagnostic items, but teachers check their curricular validity and avoid feeding sensitive student records into public systems. Second, teachers and students negotiate goals that are comprehensible and revisable; this converts personalization from opaque algorithmic placement into a transparent learning agreement.

Third, AI-generated scaffolds are bounded by explicit instructional constraints. A teacher can request two explanations of the same mathematical or linguistic concept, one using everyday language and another using a disciplinary representation, but must inspect both for accuracy and assumptions. Fourth, learners compare explanations, challenge outputs, discuss errors, and produce independent responses. This dialogic step preserves critical reasoning and peer interaction instead of replacing them with solitary chatbot use.

Fifth, the teacher gathers evidence from short retrieval tasks, oral explanations, revision histories, and learner reflection. The system may suggest feedback, but the teacher decides which errors are conceptually important. Sixth, instruction is adjusted using this evidence and students reflect on whether assistance made them more capable of independent performance. The sequence is cyclical: new evidence updates goals rather than locking learners into fixed categories.

Across these phases, the framework assigns distinct responsibilities. AI generates options and potentially useful patterns; learners make and justify choices; teachers validate disciplinary accuracy, sustain equitable participation, and interpret progress. The model does not presume that AI outputs are neutral. Educators should scrutinize stereotyped examples, inappropriate reading levels, and limited support for underrepresented languages before materials are used.

4. Discussion

An important distinction emerges between customization of instructional content and personalization of educational relationships. The former can be scaled through automation; the latter depends on trust, interpretive judgment, and shared understanding of learner needs. A large number of AI-created tasks could produce the appearance of differentiation while leaving the curriculum, classroom discourse, and assessment unchanged. The HCPP framework treats the quality of student reasoning and autonomy as higher-order criteria than the quantity of generated material.

Three implementation tensions require attention. Efficiency may conflict with deep learning when teachers accept fluent outputs without checking them. Inclusion may conflict with rapid deployment when language varieties, disability accommodations, and connectivity are neglected. Personalization may conflict with privacy when highly detailed learner profiles are collected without necessity. UNESCO (2023) offers a governance rationale for limiting data collection, involving stakeholders, and maintaining human oversight. Schools should also communicate when AI is used and establish a route for contesting inappropriate recommendations.

For future empirical research, the model suggests a cluster-randomized or carefully matched classroom comparison in which AI-supported differentiation is contrasted with teacher-designed differentiation using the same instructional objectives. Outcome measures should include independently completed assessments, improvement in explanations, students' perceived agency, teacher workload, access disparities, and incidents of inaccurate feedback. Implementation fidelity should be measured separately from learning outcomes so that low effects are not mistakenly attributed to the technology alone.

5. Practical Implications

Teacher education programs can translate the model into a short design cycle: produce an AI-assisted lesson variant, identify two likely hallucinations or biases, design a non-AI alternative, and test whether students can perform independently after support is withdrawn. Administrators should provide approved tools, clear usage policies, and time for collaborative moderation rather than treating access to a chatbot as professional development. Evaluation should prioritize observable pedagogical benefits and equitable access over platform adoption rates.

5. Classroom Implementation: Planning for Differentiation

Implementation begins with an instructional problem rather than a technology purchase. For example, an English-language teacher may identify that students can recall vocabulary but struggle to use it in context. A diagnostic sequence could ask students to interpret a short passage, explain their reasoning orally, and write a response for a familiar audience. The teacher then reviews errors and establishes two or three learning pathways. An AI system may draft contextualized dialogues at contrasting levels, but the teacher checks whether each dialogue actually illustrates the targeted linguistic feature. Such planning avoids confusing surface variety with cognitive progression. Students must also be permitted to complete equivalent activities without an AI account or personal device.

A practical lesson may use four phases: orientation, guided comparison, independent production, and reflection. During orientation, the teacher explains the goal and the limits of any AI-generated material. In guided comparison, small groups examine two explanations, locate ambiguities, and propose improvements. In independent production, learners complete a transfer task without automated suggestions. In reflection, learners identify which scaffold was useful and which was misleading. This sequence creates an observable distinction between receiving assistance and acquiring competence. A teacher can compare early and later explanations, looking not merely at correctness but at the specificity of reasoning and the appropriateness of examples.

6. Inclusion, Accessibility, and Language Equity

AI-supported personalization can improve access when it provides alternative formats, plain-language explanations, and additional practice opportunities. Yet the same system may reproduce social or linguistic inequalities. Models can underperform on local terminology, dialectal expressions, and low-resource languages; an output that appears fluent may nevertheless misrepresent cultural practices. Educators should examine whose examples and experiences are represented, whether accessibility adaptations preserve disciplinary meaning, and whether students are expected to disclose sensitive circumstances to receive support. Inclusive personalization therefore calls for choice and universal design, not compulsory profiling. A learner should be able to request help without being categorized by potentially stigmatizing characteristics.

Schools can create a minimal-risk protocol. Teachers use synthetic student profiles when testing prompts, remove identifiable records before analysis, retain only information essential to a clear educational purpose, and seek institutional approval where needed. For accessibility, the same concept may be presented as written explanation, structured vocabulary list, or teacher-led conversation. These

alternatives should be assessed against the same learning objective. AI should not become a separate lower-expectation curriculum for students with disabilities or less access to technology. Human review is essential to keep the adaptations equivalent in intellectual demand and educational dignity.

7. Evaluation and Research Agenda

The framework can be studied using a mixed-methods design. A future investigation could compare two sequences covering equivalent curricular content, one incorporating teacher-verified AI scaffolds and one relying on conventional differentiated materials. Outcome measures should include concept retention, ability to transfer knowledge to unfamiliar tasks, student explanation quality, and self-regulated learning behaviors. Classroom observations and teacher interviews could illuminate whether AI reduced preparation burden or simply shifted effort to verification. These are proposed measurements, not findings from the present article. Randomization or matched comparison may reduce selection bias, while transparent reporting of implementation fidelity would clarify what the intervention actually involved.

Further studies should document access constraints, student proficiency, discipline, and teacher experience. An intervention that works with older learners in a well-connected institution may not generalize to primary classrooms or rural settings. Researchers should explicitly report model version, prompt protocols, teacher corrections, and the use of student information, since these choices can materially alter the intervention. Long-term inquiry is particularly important: short-term satisfaction with tailored explanations is not adequate evidence of durable independence. An ethically sound evaluation also solicits student perspectives on autonomy, fairness, and whether assistance affected their willingness to persist with difficult tasks.

8. Practical Recommendations for Educational Leaders

Institutional leaders can support adoption by establishing approved use cases, review procedures, and time for collaborative lesson design. A pilot could focus on a small number of well-defined objectives, with teachers documenting an example generated by AI, the correction they made, and the resulting student task. Professional learning meetings can compare these cases to develop local standards of quality. Evaluation criteria should privilege learning evidence over counts of generated worksheets or logins. A decision to expand adoption should follow an assessment of equity, staff workload, and data stewardship, rather than simply positive impressions of technical novelty.

This approach also changes teacher professional development. Instead of one-off training on prompt formulas, teams can practice checking disciplinary errors, adapting explanations to developmental stages, designing non-AI alternatives, and discussing ambiguous cases. Students can be taught to ask how an answer was justified and when independent verification is required. Administrators should provide mechanisms for reporting inaccurate or inappropriate output without blaming teachers or learners. These routines frame AI as an accountable instructional resource whose value remains contingent on informed human decision-making.

6. Conclusion

AI can expand the repertoire of differentiated materials and formative supports, but effective personalization depends on teacher interpretation and learner participation. The proposed HCPP framework supplies six instructional phases and accompanying safeguards for human-centered implementation. Its contribution is conceptual: subsequent classroom studies must determine feasibility, equity, and measurable learning effects across subjects and educational contexts.

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