



Personalised Learning with Artificial Intelligence

Abstract :

Personalised learning—tailoring instruction to an individual learner’s needs, preferences, and pace—has gained renewed attention with advances in artificial intelligence (AI). AI techniques (machine learning, recommender systems, and intelligent tutoring systems) enable continuous diagnostics, adaptive sequencing, and individualized feedback at scale. This paper reviews recent literature on AI-driven personalised learning, synthesises common architectures and algorithms, discusses pedagogical and motivational frameworks that pair well with AI, presents a proposed integrative framework for classroom and online use, and examines ethical, technical, and evaluation challenges. Evidence suggests AI can improve learning gains in targeted contexts, but adoption requires attention to data quality, teacher roles, transparency, and fairness. Future research must prioritize rigorous experimental evaluation in real educational settings and human-centered design.

Key words:

1. Personalised learning
2. Artificial Learning in AI
3. Adaptive Learning Systems
4. Intelligent Tutoring Systems
5. AI- Driven Education.

Introduction:

Personalised learning (PL) aims to align content, pacing, and instructional strategies with each learner’s knowledge state, goals, and motivational profile. Historically, individualisation efforts were limited by teacher bandwidth; digital systems promised scale but were often rule-based and brittle. Recent advances in AI—particularly adaptive machine learning, natural language processing, and learner modelling—have created new opportunities to deliver genuine personalization across settings . However, the literature reports mixed outcomes: while many AI systems show promise in controlled experiments, robust, scalable gains in real classrooms are variable and contingent on design, context, and evaluation methods.

Definitions and Scope :

Personalised Learning (PL): Instruction that adapts content, pace, modality, and feedback to individual learners’ cognitive and affective states. AI in Education (AIED): Use of AI techniques to model learners, make pedagogical decisions, generate feedback, and automate assessment. For this paper, “AI-driven PL” refers to systems that employ adaptive algorithms (e.g., reinforcement learning, Bayesian knowledge tracing, deep learning recommenders) to individualise learning.

1 Historical approaches: ITS and rule-based systems Intelligent Tutoring Systems (ITS) originated decades ago to emulate one-on-one tutoring through domain models, student models, and pedagogical modules. Traditional ITS used explicit rules and cognitive models to select problems and provide hints; contemporary ITS integrate advanced ML models to improve student modelling and scalability. Reviews indicate that ITS can produce positive effect sizes in controlled studies, but real-world effectiveness depends on integration with pedagogy and classroom practices.



Modern AI techniques for personalisation Recent systematic reviews highlight several recurring AI approaches: Bayesian and probabilistic knowledge tracing for modelling mastery and predicting next items. Reinforcement learning to optimise sequencing of content or interventions. Collaborative filtering and recommender systems to personalise resource suggestions. NLP and automated feedback (essay scoring, dialogue systems) to support open-ended tasks. Learning analytics and predictive modelling to detect at-risk learners and adapt supports. These techniques have matured, but require careful feature engineering and longitudinal datasets. Pedagogical & motivational frameworks Technical adaptation must align with pedagogy. The ARCS model (Attention, Relevance, Confidence, Satisfaction) and other motivational frameworks have been used to design personalised learning pathways that keep learners engaged. Integrating AI with these frameworks can guide which adaptations are pedagogically meaningful (e.g., increasing challenge to build confidence, or varying modalities to sustain attention). Empirical evidence and meta-analyses Systematic reviews from the last five years show that AI-enabled personalised systems yield better outcomes in targeted domains (e.g., mathematics problem solving, language learning) but effects are heterogeneous. Positive impacts are more likely when systems provide formative assessment, Scaffolded feedback, and when teachers remain involved in orchestration. Reviews warn that many studies suffer from short durations, small samples, or lack of real-world controls. Core Components of an AI-Enabled Personalised Learning System Based on the literature, effective PL systems typically include five interlocking modules:

1. Learner Model (diagnostics): Continuously estimates knowledge, misconceptions, affective state, and engagement using multimodal data. (e.g., knowledge tracing, affect detection).
2. Content Repository & Metadata: Tagged resources (learning objects, exercises, hints) with pedagogical attributes and difficulty.
3. Policy Engine (decision maker): Uses data from the learner model to select next activities; can be rule-based, ML-based, or hybrid (reinforcement learning + pedagogical constraints).
4. Feedback & Scaffolding Module: Generates tailored feedback (worked examples, hints, corrective explanations) and adapts granularity to learner needs.
5. Teacher Dashboard & Orchestration Tools: Visualises learner progress, flags interventions, and allows human teachers to override or tune system behaviour. Human-in-the-loop designs produce better alignment with classroom goals.

Proposed Integrative Framework (Design & Implementation) This paper proposes a practical five-step framework for implementing AI-driven PL in K-12 and higher education:

1. Define instructional objectives & success metrics. Align AI actions with learning outcomes and motivational goals (e.g., ARCS components)
2. . 2. Collect representative, high-quality data. Ensure assessments map to curriculum standards; include interaction logs, assessment items, and optional affective signals.
3. 3. Develop transparent learner models. Prefer interpretable models (e.g., Bayesian knowledge tracing or attention-augmented models with explainability layers) where possible to support teacher trust.



4. Deploy hybrid decision policies. Combine pedagogical rules with ML optimisation; include safety constraints (avoid cycling students through repetitive remediation).
5. Iterate with teachers and students (human-centered design). Run pilot phases, collect qualitative feedback, and measure both learning gains and affective outcomes. Human-centred learning analytics are critical to ethically and effectively deploy AI.
6. Evaluation Strategies Robust evaluation requires a mixed methods approach: Randomized Controlled Trials (RCTs) here feasible to estimate causal impacts. A/B testing of sequencing or feedback algorithms in digital platforms. Longitudinal pre/post designs to track retention and transfer. Qualitative studies (interviews, teacher logs) to understand classroom integration and unintended outcomes. Systematic reviews note a deficit of long-term, large-scale RCTs; future work should emphasise external validity and pragmatic trials.
7. Ethical, Equity, and Operational Challenges- 7.1 Data privacy and consent Personalisation depends on rich learner data. Systems must comply with privacy regulations, obtain informed consent (or parental consent for minors), and minimize collection to what is pedagogically necessary. -7.2 Bias and fairness Models trained on biased datasets can reproduce or amplify inequalities (e.g., underestimating abilities of certain groups). Ongoing fairness audits and diverse training data are essential. - 7.3 Explainability and teacher trust Opaque algorithmic decisions undermine adoption. Providing interpretable rationales for recommendations and enabling teacher override improves transparency and acceptance. - 7.4 Pedagogical alignment and de-skilling risk Over-automation risks sidelining teachers' professional judgment. Systems should augment—not replace—teachers, offering supports that preserve teacher agency.- 7.5 Scalability and infrastructure Resource constraints (bandwidth, device availability) and maintenance costs impede large-scale rollout in many contexts; offline-capable and low-resource designs are needed.
8. Case Examples (Illustrative) Intelligent Tutoring in Math: ITS studies show improved problem solving and mastery when personalised hints and step-by-step scaffolding are provided. Effect sizes differ by domain and implementation details. Adaptive Courseware: Platforms that sequence content by mastery and recommend remedial or accelerated paths show promise for large enrollment courses, particularly in STEM. Integration with instructor dashboards increases effectiveness. Human-centred Learning Analytics: Deployments that present clear, actionable analytics to teachers (rather than raw predictions) have better uptake and more positive outcomes.
9. Recommendations for Practitioners and Policymakers -1. Prioritise teacher involvement: co-design systems with teachers and provide training. Mandate transparency standards require explainability, documented decision rules and audit logs for deployed systems.- 2. Invest in evaluation infrastructure**: fund long-term, large-scale studies and open datasets (with privacy protections). - 3.Design for equity: include underrepresented learners in data and test for disparate impacts. 4.Adopt human-centred privacy practices: minimal data collection, clear consent, and local data controls.

10. Conclusion AI offers powerful tools to personalise learning at scale—through adaptive sequencing, precision feedback, and predictive analytics. The literature demonstrates promise, especially when AI is paired with sound pedagogy and teacher orchestration. Yet, meaningful impact requires rigorous evaluation, ethical safeguards, human-centred design, and careful attention to equity and transparency. Future research should focus on long-term learning outcomes, fairness audits, and scalability in diverse educational contexts.

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