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Personalized Learning through Machine Teaching and Machine Learning: Enhancing Adaptive Educational Systems

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1. Round 1

1.1 Reviewer 1

Reviewer:

While the historical overview is informative, this paragraph should briefly connect early individualized instruction to modern AI-based personalization. Otherwise, the temporal leap from the 19th century to PLATO/TICCIT appears abrupt. A transition sentence linking these pedagogical movements to computational adaptation would improve cohesion.

This definition (Gómez et al., 2014) duplicates the preceding conceptual explanation. Consider condensing the two paragraphs into a single coherent discussion of personalized learning to avoid redundancy.

The paragraph beginning “Artificial intelligence first emerged as a research field in 1956” abruptly shifts from pedagogy to AI without synthesizing the pedagogical rationale for machine learning adoption. Add a transition emphasizing how AI bridges the gap between human differentiation and data-driven adaptivity.

This paragraph insightfully connects pedagogy and machine teaching but lacks a critical discussion of ethical implications—especially the risk of algorithmic bias when human pedagogical judgment is encoded in data. Add 2–3 sentences reflecting on this limitation.

While the table is informative, it lacks column alignment and statistical descriptors (e.g., mean, SD). The table should include a caption explaining variable types and coding schema (0 = No Decline; 1 = Decline) for clarity.

The explanation is philosophically accurate but verbose. Consider integrating a concise data-information-knowledge hierarchy model (DIKW) to clarify epistemic relationships, widely used in educational data mining literature.

This section effectively defines supervised and unsupervised learning but omits semi-supervised and reinforcement learning details, despite mentioning them. Add brief clarifications of how semi-supervised and reinforcement paradigms fit within educational contexts.

Author revised the manuscript and uploaded the updated document.

1.2 Reviewer 2

Reviewer:

This example is clear, but the text could include a visual schematic or pseudocode representing the learning pipeline (input → preprocessing → model → output) to improve technical transparency for interdisciplinary readers.

The literature review contains an excellent chronological account, but several sentences (e.g., "This developement in reasearch n this fieled…") contain typographical errors. A careful proofread is needed for consistency in capitalization, grammar, and spacing.

This section would benefit from clearer differentiation between machine teaching and curriculum learning, as readers may conflate these. Briefly explain how the "inverse problem" formulation distinguishes the two.

Equation (1.1) lacks properly defined variables (D, M, L, R). Provide a full mathematical expression using LaTeX formatting and clarify each variable immediately below. Currently, the reader cannot reconstruct the optimization framework.

This section accurately summarizes Shulman's framework but could explicitly connect how PCK can inform algorithmic data selection—e.g., by embedding PCK dimensions as feature weights or selection constraints in the machine teaching model.

This paragraph insightfully distinguishes "manipulative" from "general" learning. Expand this ethical discussion by referencing transparency, explainability, and autonomy in adaptive learning systems. It strengthens the theoretical grounding for educational application.

Author revised the manuscript and uploaded the updated document.

2. Revised

Editor's decision after revisions: Accepted.

Editor in Chief's decision: Accepted.

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