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Methodological Approaches of Machine Learning and Adaptive Personalization in Educational Gaming Platforms

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Abstract. This article presents a systematic review of methodological approaches in machine learning (ML), educational data mining (EDM), and adaptive gamification within digital learning environments. Based on a synthesis of 36 peer-reviewed studies published between 2020 and 2025, indexed in Scopus and Web of Science, this research identifies prevalent ML architectures, personalized instruction paradigms, and game mechanics that enhance student motivation. The literature search followed PRISMA guidelines across major academic databases, including IEEE Xplore, SpringerLink, MDPI, and ScienceDirect, applying rigorous inclusion criteria focused on the functional implementation of EdTech solutions. The analysis reveals a significant shift toward the integration of graph neural networks (GNNs), reinforcement learning (RL), and gradient boosting for behavioral modeling and real-time content adaptation. Findings indicate that adaptive gamification, when coupled with predictive learning analytics, substantially improves long-term student engagement compared to static models. Furthermore, this study formalizes a conceptual interaction framework between the learner, the gamified environment, and an RL-based personalization agent. The results provide a methodological foundation for developing scalable, intelligent tutoring systems capable of autonomous pedagogical decision-making.

Keywords: machine learning, educational data mining, learning analytics, adaptive gamification, personalized learning, reinforcement learning, graph neural networks.

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Introduction

In recent years, digital education platforms have increasingly integrated Artificial Intelligence (AI) paradigms, including Machine Learning (ML), Educational Data Mining (EDM), and Learning Analytics (LA), to foster personalized learning environments. These technologies facilitate the dynamic adaptation of instructional content, pedagogical feedback, and task difficulty based on individual learner profiles and real-time behavioral patterns. A substantial body of research has demonstrated the efficacy of ML-based solutions in predicting academic performance and optimizing personalization through classification algorithms, neural networks, and Reinforcement Learning (RL) to generate individualized pathways. Furthermore, gamification has emerged as a critical motivational strategy, though empirical evidence suggests that static gamification often suffers from novelty wear-off. In contrast, adaptive gamification, which utilizes ML to personalize game elements, shows significant potential in sustaining long-term engagement. Advanced computational techniques, such as Graph Neural Networks (GNNs) and deep behavioral modeling, now enable the tracking of granular user data, including clickstream analysis and churn risk, to trigger predictive interventions.

Table 1. Synthesis of Influential Studies and Methodological Contributions

Article Focus	Authors	AI/ML Methods	Key Advantages	Methodological Gaps
Scalable Adaptation	Vassoyan et al. (2023)	GNN, Reinforcement Learning	High adaptability; robust to sparse datasets	Tested on simulated data; lacks real-world validation
Learning Analytics	Tretow-Fish et al. (2022)	Systematic Review Methodology	Identifies research gaps in adaptive systems	Limited empirical validation of AI-based methods
Higher Education	Merino-Campos (2025)	Analytical Review of AI	Maps AI roles in engagement and flexibility	Ethical, privacy, and scalability issues remain
Real-time Prediction	Lamb et al. (2022)	fNIRS + ML Classification	High precision in real-time hemodynamics	Requires complex hardware; limited reproducibility
Adaptive Gamification	Manoharan et al. (2024)	RL-based Recommendations	Individualized reward logic; improved motivation	Lack of detailed algorithmic specification
EDM Taxonomies	Zhang et al. (2024)	Taxonomies (ER, CD, KT, LA)	Structured overview of knowledge tracing	Primarily descriptive; lacks predictive modeling

The taxonomic classification of these educational environments is illustrated in Figure 1, which distinguishes three primary functional categories based on their pedagogical objectives. Structured learning platforms, such as MOOCs (e.g., Coursera, Khan Academy), focus on academic knowledge acquisition, while game-based learning and assessment tools (e.g., Kahoot, Duolingo) prioritize interactivity and testing. Additionally, cognitive development systems (e.g., Lumosity, Elevate) are designed to enhance executive functions like memory and attention. This classification systematizes the diversity of current EdTech solutions, demonstrating that gamified environments serve as both supplementary aids and independent tools. However, the existing literature reveals a fragmented landscape regarding evaluation metrics and deployment scalability, as most implementations remain restricted to isolated pilot studies.

Literature Review

Following PRISMA guidelines, this study identifies key methodological contributions in the field. Table 1 synthesizes the most influential research, highlighting the shift toward autonomous, data-driven systems.

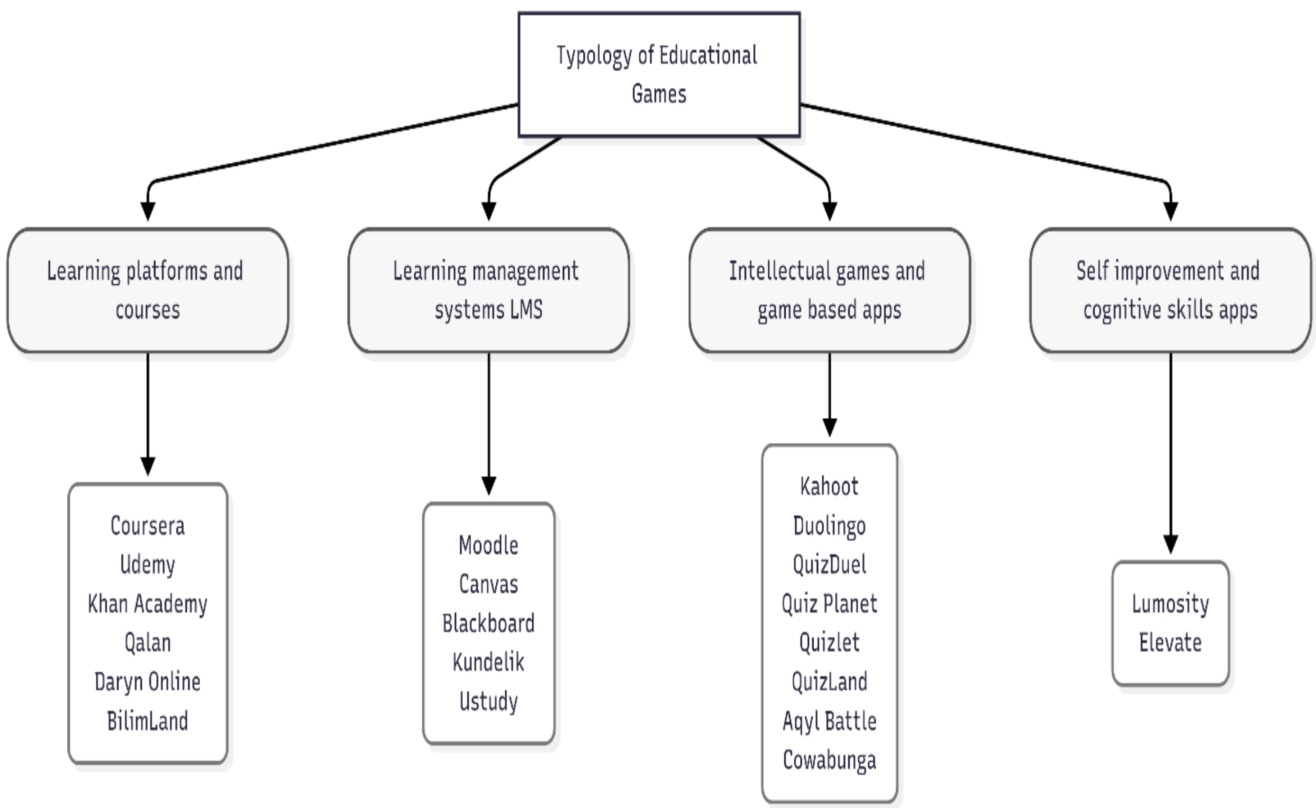

Figure 1. Typology of educational games and applications [authors' diagram]

The methodology

To ensure scientific rigor and transparency, this study was conducted in accordance with the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. The primary objective was to gain a comprehensive understanding of AI-driven personalization by identifying current technologies, evaluating their effectiveness, and outlining implementation limitations.

Search Strategy and Data Selection

The literature search targeted peer-reviewed publications from the 2020–2025 period. To maintain high academic standards and address previous methodological inconsistencies, the primary search was restricted to the Web of Science (WoS) and Scopus databases, supplemented by technical repositories including IEEE Xplore, SpringerLink, MDPI, and ScienceDirect. The search was executed in August 2024 using a Boolean query: («machine learning» OR «AI») AND («personalized learning» OR «adaptive learning») AND («gamification» OR «educational games»). Further specialized expressions were applied, such as TITLE-ABS-KEY («educational data mining» AND «gamification»), to ensure a comprehensive corpus.

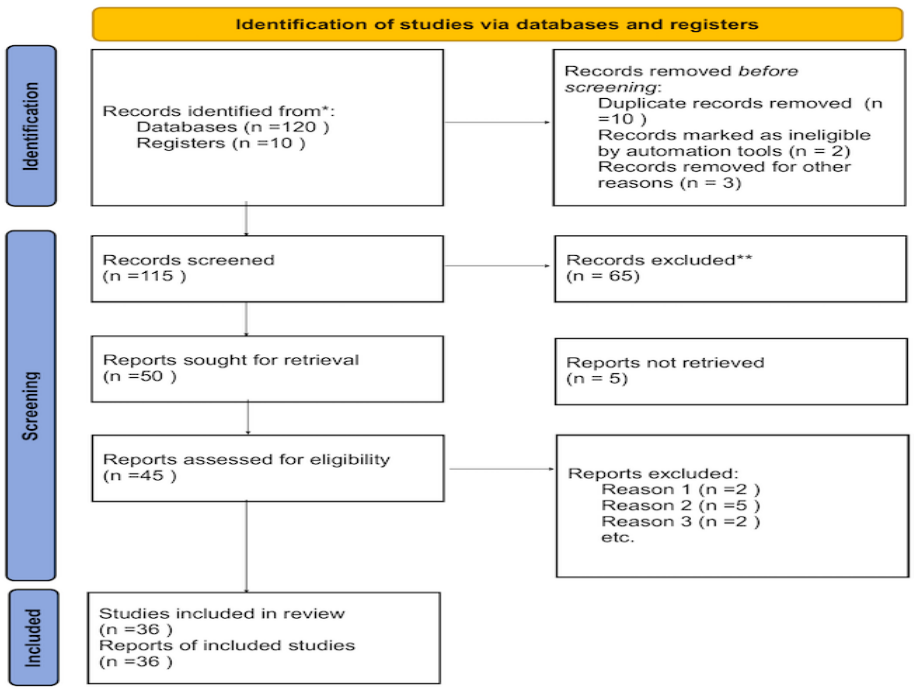

Figure 2. PRISMA flow diagram of the study identification and selection process

The identification and selection process is documented in the PRISMA flow diagram presented in Figure 2. From an initial pool of 450 records, duplicates were removed, leaving 280 items for title and abstract screening. Subsequently, 85 full-text articles were assessed against strict operational criteria. Inclusion required studies to be peer-reviewed journal articles or conference proceedings published in English, focusing on the functional implementation of AI/ML algorithms in education. Non-academic sources, preprints from non-indexed repositories, and studies unrelated to digital learning were excluded, resulting in a final selection of 36 high-quality studies.

Data Synthesis and Bibliometric Analysis

The selected studies were subjected to thematic synthesis and classified into categories: machine learning in EdTech (focusing on GNN, SVM, and Neural Networks), personalized learning systems, adaptive gamification, and educational data mining. A comparative analysis was performed for each category to identify methodological advantages and limitations. To illustrate broader research trends, a bibliometric visualization was conducted using the VOSviewer software package (version 1.6.20), as shown in Figure 3.

This visualization highlights the keyword co-occurrence network, where learning analytics emerges as the central hub linking various subfields. The analysis reveals distinct thematic clusters: a red cluster focused on data-driven approaches and adaptive systems; a blue cluster encompassing advanced machine learning paradigms like self-supervised and federated learning; and a green cluster representing learner-centered AI applications and gamification. Additionally, purple and yellow clusters point to immersive technologies and predictive analytics. This structural mapping provides the necessary context for the interaction model proposed in the following sections, which bridges the gap between raw interaction data and adaptive pedagogical interventions.

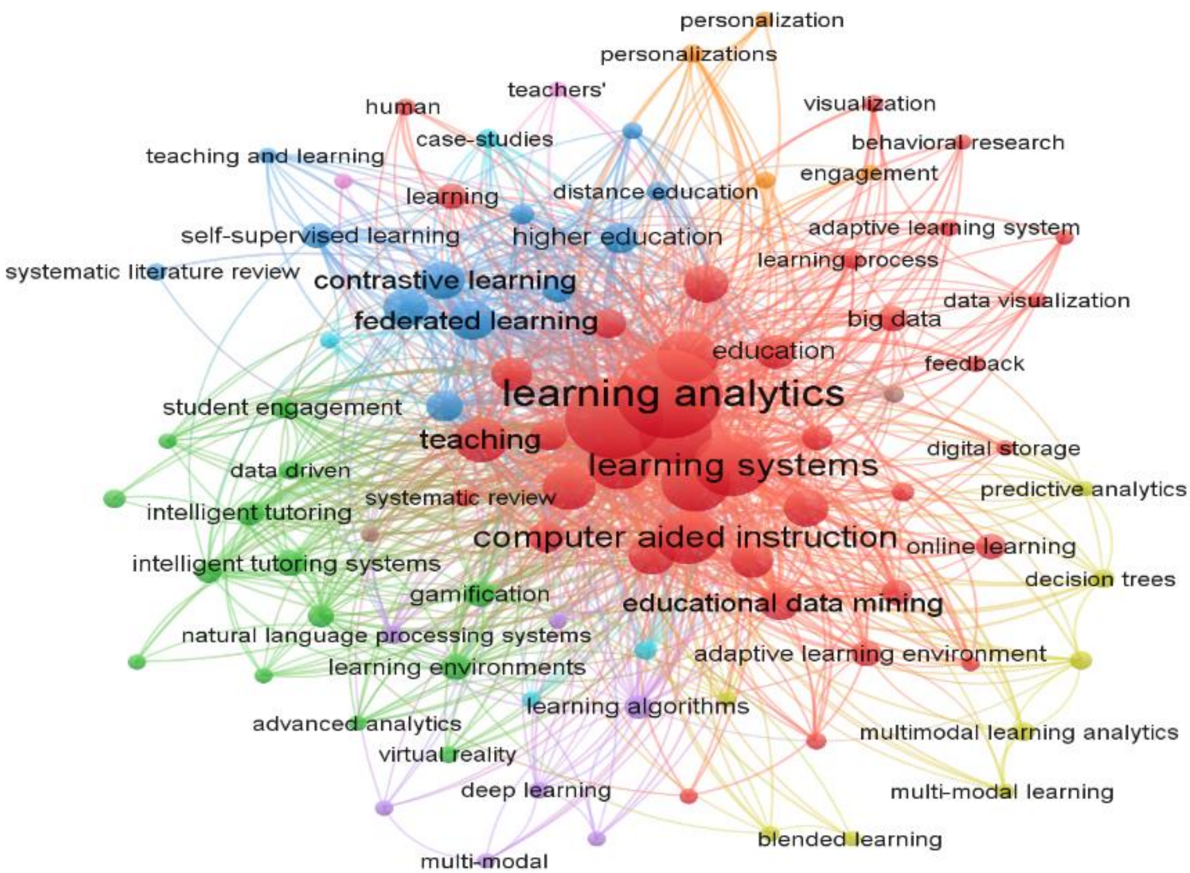

Figure 3. Visualization of scientific research in Educational Data Mining and gamification (VOSviewer)

Findings/Discussion

The comparative analysis of machine learning models identifies specific technical trade-offs critical for educational environments. Table 2 summarizes these architectures, highlighting their operational utility and inherent limitations.

The data presented in Table 2 suggests that hybrid approaches, particularly those combining Graph Neural Networks (GNN) and Reinforcement Learning (RL), are most effective for modeling complex learning paths. However, neuroanalytical techniques using fNIRS provide unparalleled precision in assessing cognitive load, though they demand significant hardware investment [29, 35]. While XGBoost is valued for its transparency in performance forecasting, deep learning architectures like LSTM and Attention networks are essential for processing high-frequency interaction sequences, albeit at a higher computational cost [9, 36].

Table 2. Comparative analysis of computational models in EdTech

Model	Primary Application	Technical Advantages	Operational Constraints
GNN + RL	Knowledge trajectories and content adaptation	High scalability and architectural flexibility	Dependency on predefined graph structures
fNIRS + ML	Neuroanalytics and cognitive state monitoring	High biometric precision and real-time adaptation	Hardware complexity and equipment costs
XGBoost	Performance analysis and predictive modeling	Statistical reliability and high interpretability	Sensitivity to dataset imbalance
LSTM/CNN/Attention	Behavioral sequences and visual content analysis	Deep temporal analysis and interaction mapping	Resource-intensive; susceptibility to overfitting

Personalized Learning Systems and Adaptive Mechanics

Personalized Learning Systems (PLSs) have evolved into fundamental EdTech components by tailoring instruction to unique learner profiles. Contemporary platforms integrate recommender algorithms and dynamic content delivery to adjust the pace and structure of curricula. Gligorea et al. (2023) demonstrated that intelligent recommender systems utilizing behavioral data significantly enhance student motivation [8]. Further research by Zhang et al. (2023) in the context of MOOCs classifies these approaches into collaborative filtering and neural models, emphasizing that adaptation grounded in cognitive parameters is the most effective method for trajectory construction [18].

This dynamic adaptation ensures that the cognitive load remains aligned with the learner's Zone of Proximal Development (ZPD). As highlighted by Merino-Campos (2025), AI allows for the real-time restructuring of materials based on language, context, and prior preparedness [34]. Moreover, the use of GNNs enables the modeling of latent connections between topics, while adaptive dashboards allow both students and instructors to monitor progress indicators, fostering active participation in the learning process [16, 35].

Adaptive Gamification and Engagement Dynamics

Gamification has transitioned from static reward structures (points and badges) to adaptive mechanics tailored to individual behavioral analytics. Strousopoulos and Troussas (2022) found that students in gamified environments demonstrate statistically significant improvements in satisfaction compared to traditional cohorts [27]. Modern algorithms now personalize game stimuli; for instance, less motivated users may receive immediate rewards for simple tasks, whereas advanced learners are challenged with complex missions and delayed gratification [5].

Table 3. Categorization of Research Directions by Technological Focus

№	Research Cluster Focus	GNN	ML	Gamification	Personalized Learning	Learning Analytics	AI/ Adaptive Learning
1	AI-Driven Personalization	-	[6, 33]	[33]	[11, 16, 25]	[16, 25, 33]	[6, 8, 10, 11, 20]
2	Learning Analytics & Success	-	[36]	[27]	[7, 17, 24, 27]	[7, 12, 17, 18, 19, 36]	[12, 18, 19, 23]
3	Gamification & Engagement	-	[4, 21]	[4, 5, 21]	[5, 21, 26, 32]	[4]	[5, 26, 32]
4	Machine Learning & Analytics	[35]	[1,9, 22,28]	-	[1, 9]	[22, 28]	[1, 9, 35]
5	Conceptual & Review Studies	-	[2, 30]	-	[2, 3, 13, 30]	[2]	[3, 13]
6	Advanced Computational Models	-	-	-	[34]	[14, 34]	[14, 15, 34]

The identification of distinct engagement styles - such as «achievement hunters», «explorers» and «social participants» - underscores the necessity of this personalization [14]. Meta-analytical data confirms that gamification is most effective when combined with real-time feedback, potentially increasing engagement by up to 30% for average-performing students [19].

Educational Data Mining and Behavioral Modeling

Educational Data Mining (EDM) serves as the analytical foundation for uncovering hidden patterns in student interaction. By analyzing LMS log files, query frequencies, and social activity, researchers can construct predictive models that forecast academic outcomes. Xu et al. (2023) identified «fatigue spots» and learner typologies (surface vs. strategic learners) using clustering techniques such as k-means and DBSCAN, alongside trajectory analysis via Markov chains [9].

These digital traces allow for the automatic segmentation of learners. Rashad Sayed et al. (2022) utilized community detection and frequency-based techniques (Apriori) to correlate study pace with assessment results, facilitating the generation of data-driven pedagogical hypotheses [28]. Furthermore, participation patterns in collaborative environments are analyzed through indicators of «active participation» such as response time and interaction frequency [31]. Typologies involving «enthusiast-explorers» or «passive participants» are often embedded into adaptive platforms using fuzzy logic, allowing for the early detection of dropout risks or disorientation.

The categorization of the reviewed studies by technological focus (Table 3) indicates that the majority of current research is concentrated in AI-driven personalization and learning analytics.

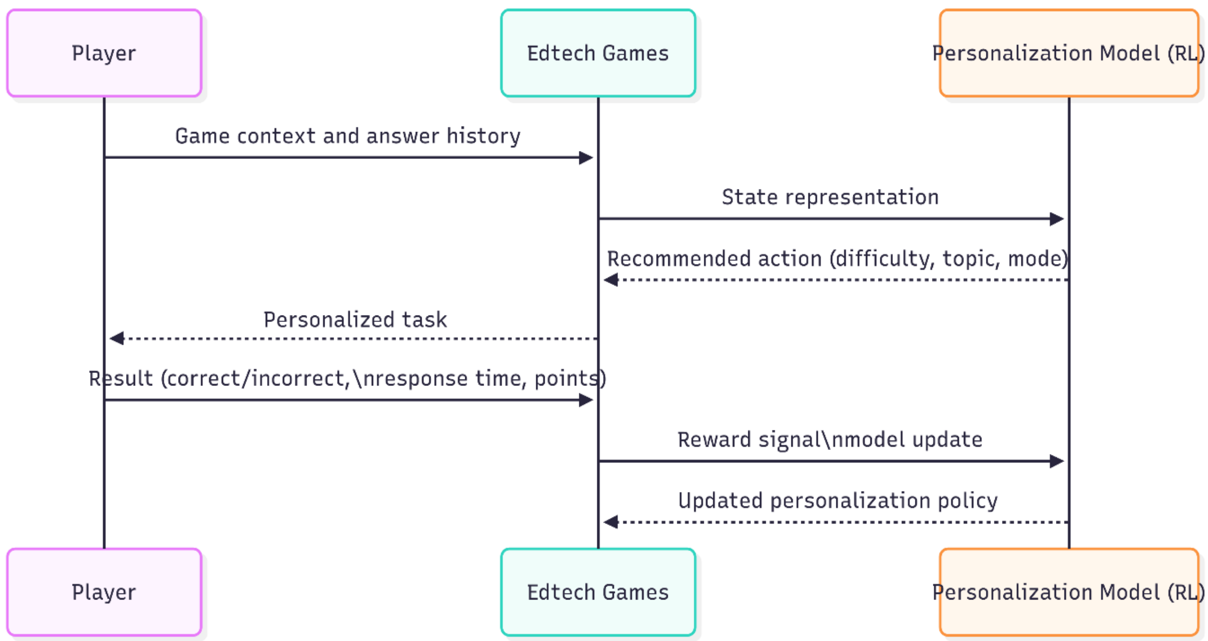

Figure 4. Interaction model of the player, EdTech game, and personalization model (RL)

Figure 4 illustrates an interactive reinforcement learning loop functioning as a dynamic, closed-loop feedback mechanism. In this model, the learning process is represented as a continuous exchange of data, where learner actions, current knowledge levels, and behavioral responses are analyzed by an intelligent personalization agent.

Based on this analysis, the algorithm automatically selects the most effective pedagogical intervention - such as adjusting difficulty levels or modifying game mechanics - which is then implemented within the educational game environment. As a result of this interaction, the system receives feedback in the form of user performance and engagement, allowing it to continuously refine the instructional strategy and create a self-optimizing learning path tailored to the individual’s cognitive characteristics.

Conclusion

The findings of this systematic review confirm that the convergence of machine learning (ML), educational data mining (EDM), and adaptive gamification represents the most significant driver of innovation in modern digital education. By synthesizing data from 36 high-impact studies published between 2020 and 2025, this research establishes that AI-driven personalization not only improves academic performance but also fundamentally reshapes student engagement through dynamic, real-time adaptation.

However, the transition from theoretical models to large-scale implementation is currently hindered by several critical barriers. High technological costs associated with biometric hardware, such as fNIRS, and the substantial computational resources required for deep learning architectures create economic obstacles for widespread adoption in public educational sectors. Furthermore, a persistent methodological gap exists: despite promising pilot results, there remains a significant lack of long-term empirical evidence regarding the cross-cultural efficacy of adaptive gamification. This is compounded by the «black-box» nature of complex neural networks, which raises substantial ethical concerns regarding algorithmic transparency, bias, and the protection of student privacy.

Looking ahead, the evolution of EdTech is clearly moving toward the integration of Explainable AI (XAI), which seeks to make personalization logic transparent and accountable to both educators and learners.

Moreover, the emergence of Large Language Models (LLMs) offers a transformative path for developing more nuanced, conversational adaptive interfaces that bridge the gap between human intuition and machine efficiency. Ultimately, the shift from descriptive learning analytics to prescriptive, agent-based models - grounded in the RL framework proposed in this study- will define the strategic trajectory of intelligent tutoring systems in the coming decade.

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The contribution of the authors

D. Zhaisanova and M. Mansurova - conceptualization,supervision

A. Kulatay; investigation, resources, writing - original draft preparation,

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