REMUNOM
ISSN 2178-6925

Received: 10/02/2026 **– Accepted:** 21/03/2026
Vol: 13.03
DOI: 10.66104/fkfg6q38
Pages: 1-25

DEVELOPMENT OF AN ARTIFICIAL INTELLIGENCE MODEL TO SUPPORT TEACHING IN DYNAMIC EDUCATIONAL ENVIRONMENTS

Rômulo Ferreira dos Santos
Ph.D. in IT Projects and Ph.D. candidate in Electrical Engineering, University of Brasília, Brazil
romulodba@gmali.com

Jaime de Melo Gama Da Silva
Master of Science in Electrical Engineering, University of Brasília, Brazil
jaime.silva@aluno.unb.br

Matheus Henrique de Souza
Public Law Specialist, University of Brasília, Brazil
sgtmhenrique@gmail.com

Paulo Cesar Rodrigues Borges
Ph.D. in Information Science and Ph.D. in Advanced Military Studies, IESB University Center, Brazil
paulo.borges@iesb.edu.br

Abstract

This article proposes an Artificial Intelligence model to support teaching in dynamic educational environments, characterized by student heterogeneity, curricular changes, and multiple modalities. The research addresses the gap in solutions that coherently integrate dynamic learning profiles, continuous progress monitoring, useful recommendations, and governance coupled with the teaching workflow. The study designs a modular, data-driven artifact evaluated in a hybrid scenario using LMS. The architecture operationalizes the cycle "data → inference → intervention → monitoring → replanning," with layers of data (logs, assessments, and metadata), intelligence (inferences and profiles), intervention (recommendations to students and support for teacher decision-making), experience (dashboards/feedback), and trust (auditing, privacy, and bias mitigation). The core of the model combines risk/proficiency prediction, a recommendation engine based on behavioral signals, and pedagogical rules. To preserve teaching autonomy and reduce socio-ethical risks, it incorporates explainability and a human-in-the-loop module to parameterize, approve, and audit recommendations. The proposed evaluation integrates technical metrics (F1, AUC, Recall@K, NDCG@K, and calibration), pedagogical impact indicators (learning gains, engagement, and teaching load), and equity audits by subgroups, aiming at responsible and sustainable adoption.

Keywords: AI in education; Learning Analytics; educational recommendation; governance and ethics.

Resumo

Este artigo propõe um modelo de Inteligência Artificial para apoiar o ensino em ambientes educacionais dinâmicos, caracterizados por heterogeneidade discente, mudanças curriculares e múltiplas modalidades. A pesquisa enfrenta a lacuna de soluções que integrem, de forma coerente, perfis de aprendizagem dinâmicos, monitoramento contínuo de progresso, recomendações úteis e governança acoplada ao fluxo de trabalho docente. O estudo concebe um artefato modular orientado por dados e avaliado em cenário híbrido com uso de LMS. A arquitetura operacionaliza o ciclo "dados

REMUNOM
ISSN 2178-6925
Received: 10/02/2026 **– Accepted:** 21/03/2026
Vol: 13.03
DOI: 10.66104/fkfg6q38
Pages: 1-25

→ inferência → intervenção → monitoramento → replanejamento”, com camadas de dados (*logs*, avaliações e metadados), inteligência (inferências e perfis), intervenção (recomendações a discentes e apoio à decisão do professor), experiência (*dashboards*/*feedback*) e confiança (auditoria, privacidade e mitigação de vieses). O núcleo do modelo combina predição de risco/proficiência, motor de recomendação baseado em sinais comportamentais e regras pedagógicas. Para preservar autonomia docente e reduzir riscos socioéticos, incorpora explicabilidade e um módulo *human-in-the-loop* para parametrizar, aprovar e auditar recomendações. A avaliação proposta integra métricas técnicas (F1, AUC, Recall@K, NDCG@K e calibragem), indicadores de impacto pedagógico (ganho de aprendizagem, engajamento e carga docente) e auditorias de equidade por subgrupos, visando adoção responsável e sustentável.

Palavras-chave: IA na educação; *Learning Analytics*; recomendação educacional; governança e ética.

Resumen

Este artículo propone un modelo de inteligencia artificial para apoyar la enseñanza en entornos educativos dinámicos, caracterizados por la heterogeneidad del alumnado, los cambios curriculares y las múltiples modalidades. La investigación aborda la falta de soluciones que integren, de manera coherente, perfiles de aprendizaje dinámicos, el seguimiento continuo del progreso, recomendaciones útiles y una gestión adaptada al flujo de trabajo docente. El estudio concibe un artefacto modular orientado a datos y evaluado en un escenario híbrido con el uso de un LMS. La arquitectura pone en práctica el ciclo “datos → inferencia → intervención → seguimiento → replanificación”, con capas de datos (registros, evaluaciones y metadatos), inteligencia (inferencias y perfiles), intervención (recomendaciones a los alumnos y apoyo a la toma de decisiones del profesor), experiencia (paneles de control/retroalimentación) y confianza (auditoría, privacidad y mitigación de sesgos). El núcleo del modelo combina la predicción de riesgo/competencia, un motor de recomendación basado en señales de comportamiento y reglas pedagógicas. Para preservar la autonomía docente y reducir los riesgos socioéticos, incorpora explicabilidad y un módulo “human-in-the-loop” para parametrizar, aprobar y auditar las recomendaciones. La evaluación propuesta integra métricas técnicas (F1, AUC, Recall@K, NDCG@K y calibración), indicadores de impacto pedagógico (ganancia de aprendizaje, compromiso y carga docente) y auditorías de equidad por subgrupos, con el objetivo de una adopción responsable y sostenible.

Palabras clave: IA en la educación; Análisis del Aprendizaje; recomendaciones educativas; gobernanza y ética.

1. Introduction

The growing digitization of education, the consolidation of hybrid learning models, and the accelerated updating of curricula and skills have shaped dynamic educational environments in which multiple student profiles, different learning paces, and diverse forms of technology-mediated pedagogical interaction coexist (CORTEZ, 2023; DA SILVA *et al.*, 2022; BAYAGA, 2024). In such contexts, whether

REMUNOM
ISSN 2178-6925
Received: 10/02/2026 **– Accepted:** 21/03/2026
Vol: 13.03
DOI: 10.66104/fkfg6q38
Pages: 1-25

in-person, hybrid, or virtual, the heterogeneity of prior knowledge, learning styles, and sociocultural conditions challenges standardized instructional models, demanding more flexible and responsive pedagogical arrangements (BAETA; PEDRO, 2019; DWI; HIDAYATULLAH, 2024). Additionally, the centrality of inclusion as a quality requirement reinforces the need for strategies that consider diversity, accessibility, and equity from the very design of educational practices and resources (AKBAR *et al*., 2023; KHAZANCHI; KHAZANCHI, 2021).

From a technological standpoint, AI applied to education enables the modeling of learning profiles and the analysis of large volumes of educational data, allowing for the timely and individualized adaptation of content, pace, and teaching strategies (ARMAS, 2023; IMAN *et al*., 2024; PATIL; GUPTA, 2019). In this context, educational recommendation systems have been used to suggest content, activities, and learning paths based on history, preferences, and performance, contributing to personalization and engagement (EMBARAK, 2021; LIU, 2023; ZHANG; KAMSIN, 2024). In parallel, the use of dashboards and data-driven interventions strengthens continuous monitoring, while predictive techniques support the anticipation of risks such as low performance, dropout, and disengagement, enabling initiative-taking interventions (VIGENTINI *et al*., 2017; OTU et al., 2024).

Despite advances in intelligent platforms and tools, a practical and scientific gap persists regarding the integration, within a single model, of mechanisms that combine continuous adaptation to context, actionable recommendations, and large-scale assessment, without compromising pedagogical validity or utility for teachers (APETORGBOR *et al*., 2024). Furthermore, there is a growing understanding that such solutions should enhance, rather than replace, the teacher's role, offering interpretable support for pedagogical decisions while preserving pedagogical autonomy and control (AGUILAR YUSTE; ROJAS-SÁNCHEZ, 2024; TAUFIKIN *et al*., 2024; NODZYŃSKA-MOROŃ, 2024). Finally, implementation in real-world settings requires safeguards addressing privacy and data security, bias mitigation, transparency, regulatory compliance, infrastructure limitations, and institutional resistance, factors that must be addressed from the model's design phase onward (JOSE, 2024; MESSAOUDI, 2024).

REMUNOM
ISSN 2178-6925

Received: 10/02/2026 **– Accepted:** 21/03/2026
Vol: 13.03
DOI: 10.66104/fkfg6q38
Pages: 1-25

1.1. Research problem and gap

Although there are significant initiatives in the field of AI applied to education, there remains a gap in the development of solutions capable of operating seamlessly in highly dynamic environments. There is a challenge in reconciling, within a single model: (i) personalization based on dynamic learning profiles; (ii) continuous monitoring of progress and engagement; (iii) recommendations with pedagogical utility; and (iv) governance, transparency, and effective integration into teaching practice.

Given this, the central problem of this study is defined as follows: how to develop an AI model that provides effective support for teaching in dynamic educational environments, reconciling personalization, monitoring, and recommendations with governance, transparency, and integration into teaching practice?

1.2. General and specific objectives

The overall objective of this article is to develop and describe an AI model to support teaching in dynamic educational environments, focused on personalization, continuous monitoring of student progress, and pedagogical decision support, while considering requirements for inclusion and ethical and secure implementation.

To achieve this objective, the following specific objectives are defined:

1. Model learning profiles and contextual variables.

2. Implement recommendation and pedagogical support mechanisms for teachers and students, based on evidence and focused on responsiveness.

3. Integrate automated assessment and feedback functionalities, aiming for agility and feedback in the teaching-learning process.

4. Define governance and ethical guidelines, addressing privacy, bias mitigation, minimum infrastructure requirements, and transparency.

REMUNOM
ISSN 2178-6925

Received: 10/02/2026 **– Accepted:** 21/03/2026
Vol: 13.03
DOI: 10.66104/fkfg6q38
Pages: 1-25

2. Theoretical background

2.1. Artificial Intelligence in Education: Applications and Transformative Potential

AI has established itself as a key technology in education by automating analyses, supporting decision-making, and reshaping the planning, delivery, and assessment of instruction, from advanced features in LMS platforms to adaptive and personalized interactions, thereby enhancing the responsiveness of the educational ecosystem (TRIVEDI, 2023). The most common applications include recommendation systems, intelligent tutors, and personalization supported by learning analytics, with a focus on building student profiles and adapting learning paths and interventions (EMBARAK, 2021). Additionally, predictive models enable the identification of patterns associated with dropout, low performance, and disengagement, facilitating evidence-based proactive interventions, provided they are supported by consistent data and contextualized interpretation (MAROUF *et al*., 2024).

2.2. Dynamic educational environments: heterogeneity, change, and teacher mediation

Contemporary educational settings tend to operate under conditions of high variability: heterogeneous classes, varying paces, various levels of autonomy, and multiple forms of participation challenge standardized instructional models and call for adaptive strategies. This dynamism is intensified by curricula and competencies that are constantly evolving and by digital ecosystems that frequently reconfigure practices and resources, requiring instructional planning that is revisable and context-sensitive. In this scenario, teacher mediation assumes a strategic role, with the teacher acting as an evidence-based curator and guide; however, the effectiveness of this dynamic depends on digital competencies, data literacy, and minimum structural conditions, in addition to overcoming institutional resistance to change and training limitations (DA SILVA *et al*., 2022; CORTEZ, 2023).

REMUNOM
ISSN 2178-6925
Received: 10/02/2026 **– Accepted:** 21/03/2026
Vol: 13.03
DOI: 10.66104/fkfg6q38
Pages: 1-25

2.3. Personalization and data-driven learning

Personalization is essential for equity and effectiveness in diverse settings, as it enables educational decisions to account for differences in performance, engagement, study habits, and specific needs. Based on educational and interaction data, AI models can build dynamic profiles and recommend learning paths, content, and activities, adjusting sequence, difficulty, and presentation format in a timely manner; simultaneously, recommendations can support "how to teach" by suggesting strategies and paces compatible with distinct levels of autonomy. In dynamic environments, this data-driven approach facilitates responsive and scalable interventions, if teacher mediation and the pedagogical coherence of the recommendations are maintained (KAMSIN, 2024).

2.4. Machine Learning and Learning Analytics: Prediction, Diagnosis, and Recommendations

Advances in machine learning are expanding the scope of educational AI by transforming learning logs and data into actionable insights for risk prediction, gap diagnosis, and intervention recommendations. Reviews in educational data mining and learning analytics highlight the role of data pipelines and indicators in supporting predictive and prescriptive models; however, the choice of algorithms involves trade-offs between performance and interpretability, which are essential for responsible pedagogical use. Interpretable and/or incremental approaches may facilitate the extraction of useful rules and foster teacher confidence, while real-time monitoring solutions support early warnings and targeted actions in highly variable scenarios (MAROUF *et al*., 2024; SCALISE *et al*., 2023).

2.5. Teacher support and smart platforms

In data-driven approaches, AI tends to support teaching as a catalyst: it reduces the administrative burden and informs pedagogical decisions through recommendations, alerts, and summaries. Dashboards help identify patterns and anomalies, enabling timely interventions; additionally, planning support solutions can suggest strategies and resources aligned with competencies and class profiles. In the area of feedback, NLP techniques and architectures applied to massive courses point

REMUNOM
ISSN 2178-6925

Received: 10/02/2026 **– Accepted:** 21/03/2026
Vol: 13.03
DOI: 10.66104/fkfg6q38
Pages: 1-25

the way toward faster and more personalized feedback, but their sustainable adoption depends on integration with LMS, interoperability, usability, and suitability for the pedagogical context (VIGENTINI *et al*., 2017; SCHÖNBERGER et al., 2022).

2.6. Inclusion, accessibility, and democratization

AI can advance inclusion initiatives by enabling accommodations and assistive technologies that expand access and participation for students with disabilities and special needs. Resources such as automatic sign language translation, speech recognition/synthesis, and screen reader-compatible interfaces point to gains in accessibility; similarly, language and presentation adaptations can support students with learning disabilities and historically marginalized groups. In contexts of vulnerability, the democratization of access depends on lightweight solutions, as well as realistic infrastructure planning to avoid exacerbating inequalities (AKBAR *et al*., 2023; SAYARI, 2024).

2.7. Ethical and technical challenges: privacy, bias, infrastructure, and transparency

The implementation of AI in education requires governance from the design stage: personalization and monitoring rely on personal and behavioral data, increasing the risks of surveillance and rights violations in the absence of consent, data minimization, access controls, and clear security policies. Furthermore, algorithmic biases can reproduce or amplify inequalities, making evaluation by subgroups and mitigation strategies necessary; at the same time, transparency and explainability are prerequisites for accountability and responsible pedagogical use. Finally, infrastructure constraints limit outcomes and may exacerbate disparities, requiring viable solutions that align with the institutional and regulatory context (JOSE, 2024).

2.8. Automated evaluation and feedback: efficiency and precautions

AI-powered e-assessment systems can increase the agility and scalability of assessment by combining automated grading with the analysis of written work using natural language processing (NLP); rubrics and assessment frameworks can also be

REMUNOM
ISSN 2178-6925
Received: 10/02/2026 **– Accepted:** 21/03/2026
Vol: 13.03
DOI: 10.66104/fkfg6q38
Pages: 1-25

implemented to enhance standardization and transparency. However, pedagogical validity, reliability, and fairness depend on quality data, clear criteria, and human oversight, avoiding metric reductionism and opaque decisions. Thus, automation tends to be more robust when oriented toward the formative nature of assessment and when combined with explanation and auditing mechanisms (APETORGBOR *et al*., 2024).

2.9. Impacts on teacher education and summary of requirements

The adoption of AI is reshaping teachers' competencies: beyond technical proficiency, it requires a critical understanding of limitations, risks, biases, and pedagogical applications, as well as data literacy to interpret dashboards, recommendations, and learning evidence. Studies on the role of teachers and the challenges of teaching in the age of AI converge in indicating that technology should enhance, not replace, teacher autonomy, requiring ongoing professional development and institutional strategies for responsible adoption (TANG, 2024; SEPTIANI; RAMADANI, 2025).

3. Methodology

3.1. Type of research and methodological design

This study is applied and guided by the Design Science Research (DSR) paradigm, as it aims to design, develop, and validate a technological artifact: an AI model to support teaching in dynamic educational environments. The study design employs iterative cycles of (i) gathering pedagogical and functional requirements; (ii) developing components; (iii) technical validation; and (iv) applied evaluation in a real-world scenario, using a quasi-experimental design that compares groups with and without the model's support, in line with the literature describing AI's potential for personalization, data-driven interventions, and support for teaching in digital ecosystems (TRIVEDI, 2023; PATIL; GUPTA, 2019).

REMUNOM
ISSN 2178-6925
Received: 10/02/2026 **– Accepted:** 21/03/2026
Vol: 13.03
DOI: 10.66104/fkfg6q38
Pages: 1-25

3.2. Educational landscape

The implementation is intended for a hybrid setting, preferably in higher education, using an LMS capable of recording interaction logs, facilitating assessments, and organizing instructional resources. This arrangement facilitates the continuous collection of evidence for learning analytics, monitoring, and responsive interventions, aligning with discussions on pedagogical innovation mediated by emerging technologies and AI in university settings (KUMAR *et al*., 2025; BAYAGA, 2024).

3.3. Participants and context

The empirical evaluation was conducted in a higher education institution offering hybrid undergraduate courses supported by an LMS. The study involved 298 students distributed across four classes, as well as nine instructors who used the teaching-support dashboard during the intervention phase. The intervention lasted 12 weeks, allowing the monitoring of learning trajectories, interaction patterns, and teaching decisions over time.

Participants were divided into a control group (149 students) and an intervention group (149 students) . The control group followed the regular instructional workflow supported only by the LMS native resources, whereas the intervention group used the proposed AI model to support risk detection, recommendation of pedagogical actions, and dashboard-based monitoring. Group assignment followed a quasi-experimental design based on comparison, since random allocation was not feasible in the institutional setting.

The institutional context is characterized by heterogeneous student profiles in terms of prior knowledge, access conditions, and digital learning behavior. To reduce confounding effects, the study recorded baseline academic performance, previous LMS experience, attendance patterns, and access frequency. Inclusion criteria comprised students regularly enrolled in the selected course units and active in the LMS during the study period. Exclusion criteria included incomplete enrollment records, prolonged inactivity in the platform, or missing pre- and post-test data above [threshold]%.

The characterization of the context includes baseline performance, prior

REMUNOM
ISSN 2178-6925
Received: 10/02/2026 **– Accepted:** 21/03/2026
Vol: 13.03
DOI: 10.66104/fkfg6q38
Pages: 1-25

experience with technologies, and access conditions, to interpret results and reduce the effects of infrastructural inequalities; additionally, the need for teaching competencies related to data literacy and the critical use of AI in pedagogical work is considered. Ethical aspects are treated as project requirements (NODZYŃSKA-MOROŃ, 2024).

3.4. Data pipeline, variables, and model training

The data pipeline was structured into five stages: (i) extraction, (ii) preprocessing, (iii) feature engineering, (iv) model training and validation, and (v) inference and pedagogical delivery (EMBARAK, 2021; MORALES-CHAN *et al*., 2024).

In the extraction stage, the system collected LMS interaction logs, assessment records, pedagogical metadata, and dashboard usage traces. Raw data included number of logins, session duration, page views, content access sequence, assignment submissions, quiz attempts, deadlines compliance, forum participation, feedback consultation, grades, and competency tags associated with each activity.

In the preprocessing stage, duplicated records were removed, timestamps were standardized, and missing values were managed using median imputation depending on the variable type. Outliers related to anomalous session duration or bot-like interaction patterns were filtered using z-score threshold. Data were then aggregated into weekly windows to capture learning dynamics in a time-sensitive manner.

Feature engineering generated four groups of variables. The first group comprised behavioral engagement features, such as frequency of access, average session duration, number of late submissions, inactivity gaps, and persistence in repeated attempts. The second group included performance features, such as quiz scores, formative assessment averages, progression by competency, and error recurrence by topic. The third group contained trajectory features, such as change in performance over time, trend slope, learning stability, and temporal volatility. The fourth group comprised contextual and pedagogical variables, including class modality, instructional unit, activity type, and baseline proficiency.

The predictive module addressed two supervised tasks: risk prediction and

REMUNOM
ISSN 2178-6925
Received: 10/02/2026 **– Accepted:** 21/03/2026
Vol: 13.03
DOI: 10.66104/fkfg6q38
Pages: 1-25

mastery estimation. For risk prediction, the target variable was defined as the probability of low performance or disengagement in the subsequent instructional window. For mastery estimation, the target corresponded to the probability of achieving the expected competency level in the next assessment cycle. The algorithms evaluated were Logistic Regression, Random Forest, and XGBoost/Gradient Boosting, selected to balance interpretability and predictive performance. Hyperparameter tuning was performed through grid search with stratified k-fold cross-validation (k = 5) on the training set. Model selection considered AUC-ROC, F1-score, calibration, and interpretability.

The recommendation engine adopted a hybrid strategy combining:

(a) a content-based ranking layer, based on similarity between student profile vectors and pedagogical metadata of resources;

(b) a behavior-aware prioritization layer, using recent interaction signals such as inactivity, repeated failure, and reduced engagement; and

(c) a rule-based pedagogical layer, defined by teachers to preserve curricular coherence and instructional intent.

Recommendation scores were computed as a weighted combination of model output, recent behavioral evidence, and pedagogical constraints:

Recommendation Score = w1 (predictive relevance) + w2 (behavioral urgency) + w3 (pedagogical priority), where weights were set initially as 0,33, 0,33, and 0,34, and subsequently refined with instructor feedback during the pilot phase.

For automated feedback support, the system used rubric-linked feedback templates associated with competency gaps and common error patterns. These feedback messages were not autonomously released in high-stakes situations; instead, they were submitted to the instructor through the human-in-the-loop module for approval, editing or rejection (SHIELDS, 2023; APETORGBOR *et al.*, 2024).

3.5. Metrics and evaluation criteria

The evaluation incorporates technical, pedagogical, and socio-ethical dimensions. On the technical front, prediction metrics (accuracy, precision, recall, F1, AUC, and calibration) are used where applicable, along with recommendation metrics (Precision@K, Recall@K and NDCG@ K), and stability indicators, considering that incremental and interpretable approaches can enhance reliability and suitability for

REMUNOM
ISSN 2178-6925
Received: 10/02/2026 **– Accepted:** 21/03/2026
Vol: 13.03
DOI: 10.66104/fkfg6q38
Pages: 1-25

dynamic scenarios (OTU *et al*., 2024).

On the pedagogical level, we analyze learning gains, performance on assessments, and progress by competency, as well as engagement and risk indicators, in line with discussions on performance monitoring and data-driven interventions (REKHA *et al*., 2024; MAROUF *et al*., 2024).

In terms of usability and integration into teaching practice, there has been a reduction in administrative workload and effective adoption, while maintaining the teacher's significant role in the decision-making process. (ROJAS-SÁNCHEZ, 2024; SCHÖNBERGER et al., 2022).

Finally, regarding ethical and governance criteria, privacy and security, equity auditing by subgroups, and bias mitigation are evaluated, in addition to explainability to justify recommendations/decisions to teachers and administrators (JOSE, 2024; MESSAOUDI, 2024; IGNJATOVIĆ, 2024).

4. Architecture of the proposed solution

The solution is designed as a modular, data-driven system capable of supporting personalization and continuous monitoring in dynamic educational environments. It assumes that the effectiveness of the support depends on the integration of learning evidence and its conversion into actionable information for teachers and students, according to the literature on learning analytics and educational data mining (SILVA; JANES, 2023).

4.1. System Overview

The architecture is organized into functional layers that enable the complete cycle of "data → inference → intervention → monitoring → replanning" (Figure 1).

1. Data Layer: integrates data from the VLE/LMS (access logs, time spent on tasks, attempts, and submissions), assessments (quizzes/assignments), and pedagogical metadata (competencies, objectives, and learning paths) (MAROUF *et al*., 2024; OTU *et al*., 2024).

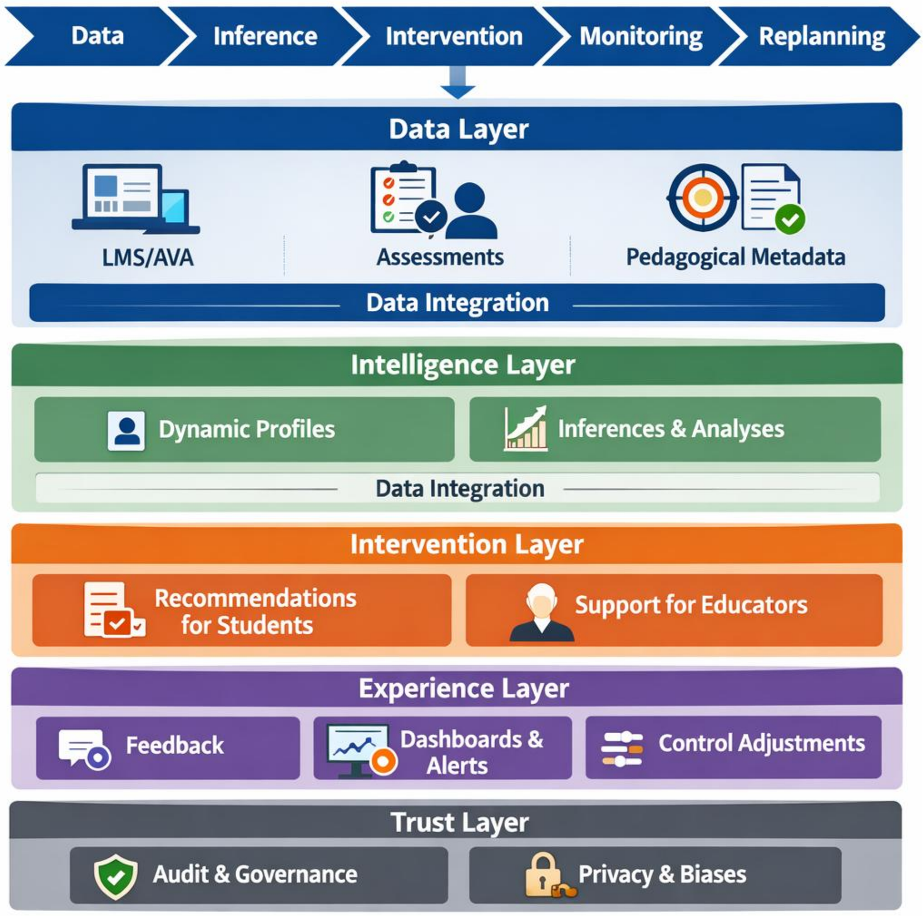
2. Intelligence Layer: builds dynamic learning profiles and generates inferences.

3. Intervention Layer: orchestrates recommendations for students

REMUNOM
ISSN 2178-6925
Received: 10/02/2026 – **Accepted:** 21/03/2026
Vol: 13.03
DOI: 10.66104/fkfg6q38
Pages: 1-25

(content/activities/pathways) and for instructors (intervention suggestions, regrouping, reinforcement, and replanning) (LIU, 2023; SCHÖNBERGER *et al*., 2022).

Figure 1: System Overview



Source: authors.

4. Experience Layer: provides actionable interfaces: feedback to students and, for teachers, dashboards, alerts, and adjustment controls (REKHA *et al*., 2024; MAROUF *et al*., 2024).

5. Trust Layer: focuses on auditing, validation, data governance, privacy, and bias mitigation, considering risks related to surveillance, algorithmic discrimination, and infrastructure dependency (JOSE, 2024; SAYARI, 2024).

4.2. Representation of the dynamic context

To reflect the changing nature of the environment, the solution adopts a time-series context model, enabling the analysis of trajectories. This design is consistent

REMUNOM
ISSN 2178-6925
Received: 10/02/2026 **– Accepted:** 21/03/2026
Vol: 13.03
DOI: 10.66104/fkfg6q38
Pages: 1-25

with continuous monitoring systems and with the need to preserve interpretive validity when data and instructional practices change over time (MAROUF *et al*., 2024).

Operationally, the system is designed to detect degradation using sliding windows, trigger alarms when metrics fall below thresholds, and perform recalibration routines based on pedagogical and governance criteria, as a means of maintaining analytical quality and reducing the risks of inappropriate automated decision-making (IGNJATOVIĆ, 2024).

4.3. Proposed AI Model

The proposed model is a socio-technical AI artifact composed of three computational cores and one governance layer.

First, the predictive core estimates the probability of academic risk and competency mastery using supervised machine learning models trained on educational log data and assessment records. After comparative testing, XGBoost achieved the best trade-off between discrimination and calibration for risk prediction, whereas Random Forest provided the most stable performance for mastery estimation across instructional windows.

Second, the recommendation core generates ranked pedagogical suggestions for both students and instructors. For students, the engine recommends activities, content objects, and learning pathways based on predicted needs and recent behavior. For instructors, it recommends intervention actions such as targeted review, regrouping, reinforcement, differentiated pacing, or follow-up with specific learners. Unlike purely automated recommenders, the present model integrates pedagogical rules defined by instructors and curriculum metadata, ensuring that recommendations remain instructionally coherent.

Third, the feedback support core links performance evidence to rubric-based feedback suggestions. This module supports formative assessment by accelerating the identification of recurring misconceptions and by proposing personalized feedback aligned with expected competencies (LIU, 2023).

The artifact operates under a human-in-the-loop architecture. Teachers can inspect explanations, approve or reject recommendations, adjust thresholds, and register pedagogical justifications. Explainability was implemented through feature

REMUNOM
ISSN 2178-6925
Received: 10/02/2026 **– Accepted:** 21/03/2026
Vol: 13.03
DOI: 10.66104/fkfg6q38
Pages: 1-25

importance summaries, temporal trajectories, and local explanations indicating the main factors associated with a given alert or recommendation (KONADE *et al*., 2024).

4.4. Mechanisms of explainability and pedagogical control

The model's effectiveness depends on practical interpretability: results must be understandable, verifiable, and actionable by teachers and students. Thus, the solution incorporates explainability and transparency as design requirements, aligning with XAI approaches and governance in AI-based educational systems (SONG *et al*., 2024; DU, 2022).

• For teachers: evidence-based justifications and temporal evolution, supporting instructional decisions and re-planning (MAROUF *et al*., 2024).

• For students: action-oriented explanations and accessibility as a design constraint where applicable (KHAN, 2024).

A human-in-the-loop module allows the teacher to set objectives, impose constraints, approve/edit recommendations, and record justifications (instructional audit). This human control acts as a safeguard regarding privacy, biases, regulatory compliance, and infrastructure limitations (JOSE, 2024; SAYARI, 2024).

5. Evaluation and results

The empirical evaluation combined technical performance, educational impact, usability, and equity analysis (APETORGBOR et al., 2024). Overall, the results indicate that the proposed model achieved satisfactory predictive performance and generated positive educational effects when used as a teacher-support system rather than as an autonomous decision-maker (CASALINO et al., 2023; MAROUF et al., 2024).

5.1. Technical evaluation of the model

The technical evaluation covers the core modules, applying appropriate metrics to each task and acknowledging trade-offs between performance, interpretability, and reliability in educational data (SCALISE; MALCOM; KAYLOR, 2023).

For the risk prediction task, the best-performing model achieved AUC-ROC =

REMUNOM
ISSN 2178-6925
Received: 10/02/2026 **– Accepted:** 21/03/2026
Vol: 13.03
DOI: 10.66104/fkfg6q38
Pages: 1-25

0,88, F1-score = 0,82, precision = 0,79, and recall =0,85 on the test set. Calibration analysis yielded a Brier Score of 0,12 and an Expected Calibration Error of 0,04, indicating that the predicted probabilities were sufficiently dependable for prioritizing pedagogical follow-up. (OTU *et al*., 2024).

For mastery estimation, the selected model obtained AUC-ROC = 0,86, F1-score = 0,81, and balanced accuracy = 0,83, with stable performance across temporal validation windows. The temporal validation design showed a performance variation of only 3,5% between training and future testing windows, suggesting acceptable robustness in dynamic educational settings (LIU, 2023; ZHANG; KAMSIN, 2024).

For the recommendation component, offline evaluation showed Recall@5 = 0,72, Recall@10 = 085, NDCG@5 = 0,68, and NDCG@10 = 0,74 (SCALISE; MALCOM; KAYLOR, 2023). In addition, recommendation coverage reached 82%, while diversity and novelty indicators suggested that the engine did not over-concentrate on a narrow set of resources. These findings indicate that the hybrid recommendation strategy was able to retrieve pedagogically relevant items while preserving a reasonable level of variety (KUMAR *et al*., 2025).

5.2. Educational and impact assessment

To assess pedagogical effectiveness, the study compared the control and intervention groups in terms of learning gains, engagement, and teacher workload. Students in the intervention group showed higher post-test performance (M = 8.2, SD = 1.1) than those in the control group (M = 6.7, SD = 1.4]). The difference was statistically significant (Mixed model coefficient (β) = 1.5, p-value < 0.001), with an effect size of Cohen’s d = 0.85 (AGUILAR YUSTE; ROJAS-SÁNCHEZ, 2024).

Learning gain analysis, based on pre and post-test differences, also favored the intervention group (Δ = 3.8) over the control group (Δ = 2.1). Engagement indicators showed that students exposed to the AI-supported workflow had 25% more regular access patterns, 40% fewer inactivity gaps, and a higher completion rate of recommended activities (88% vs 62%) (KALYUGA, 2012).

A complementary analysis of teacher workload indicated a reduction in time spent identifying at-risk students and organizing targeted interventions. Instructors reported a decrease of 45% in time spent on manual monitoring and a perceived

REMUNOM
ISSN 2178-6925

Received: 10/02/2026 **– Accepted:** 21/03/2026
Vol: 13.03
DOI: 10.66104/fkfg6q38
Pages: 1-25

increase in the timeliness of pedagogical action, although they maintained control over final intervention decisions (REKHA *et al*., 2024).

When the design involved repeated measurements, the results were further examined using [repeated measures ANOVA / linear mixed-effects models], with group as a between-subject factor and time as a within-subject factor (MORALES-CHAN *et al*., 2024). The group × time interaction was significant ($\chi^2 = 18.5$, $p < 0.001$), indicating that the intervention group improved more consistently over the experimental period than the control group (VIGENTINI *et al*., 2017).

5.3. Equity and subgroup analysis

Given the risks of algorithmic discrimination and the need for fairness and auditability, the evaluation incorporates an explicit equity component, aligned with discussions on bias, data protection, and ethical and regulatory implications of AI use in education (JAIN; MENON, 2023; IGNJATOVIĆ, 2024).

To evaluate fairness, model performance was disaggregated by relevant subgroups, including prior performance band and first-generation status. The predictive model showed limited variation across subgroups, with AUC differences below 0.03 and calibration gaps below 0.05. However, subgroup prior performance band: low presented a comparatively higher false-negative rate, indicating that some at-risk students were less frequently identified (JAIN; MENON, 2023).

To mitigate this issue, the study applied threshold adjustment, after which the disparity in false-negative rates was reduced from 0.12 to 0.04 (JAIN; MENON, 2023; SONG *et al*., 2024). These findings reinforce the need for continuous auditing, especially in educational contexts marked by heterogeneous participation and unequal access conditions (JOSE, 2024; SILVA; JANES, 2023).

5.4. Comparison with existing educational systems

The proposed model was also compared with three reference conditions: (i) native LMS analytics, (ii) a rule-based early warning workflow, and (iii) a conventional content recommender without pedagogical governance.

Compared with native LMS analytics, the proposed model offered superior temporal sensitivity and more actionable outputs, since it combined predictive signals,

REMUNOM
ISSN 2178-6925
Received: 10/02/2026 **– Accepted:** 21/03/2026
Vol: 13.03
DOI: 10.66104/fkfg6q38
Pages: 1-25

pedagogical metadata, and human validation. Compared with the rule-based workflow, it improved detection accuracy and reduced false alerts, especially in cases where low engagement did not immediately translate into low performance. Compared with a conventional recommender, the proposed model achieved better pedagogical alignment because recommendations were filtered by competency structure and teacher-defined instructional rules.

Therefore, the main originality of the artifact does not lie only in prediction or recommendation taken separately, but in the integrated articulation of prediction, recommendation, explainability, pedagogical control, and governance within a dynamic instructional workflow.

6. Discussion

6.1. Interpretation of the findings: pedagogical and technological implications

The findings indicate that the proposed model adds value primarily when it operates as a teacher-centered socio-technical decision-support system, rather than as an autonomous prescriptive mechanism. From a pedagogical perspective, the main benefit lies in improved instructional responsiveness: dynamic profiling, risk estimation, and recommendation ranking enabled earlier identification of difficulties and more timely instructional intervention. The positive differences observed between the control and intervention groups suggest that the system's value is not restricted to technical prediction quality, but extends to measurable improvements in classroom management and learning support (PATIL; GUPTA, 2019).

From a technological standpoint, the study shows that hybrid integration between supervised prediction, recommendation ranking, and rule-based pedagogical filtering can convert LMS traces into actionable instructional signals. However, the results also confirm that algorithmic performance alone is insufficient. The practical utility of the model depended strongly on data quality, feature relevance, calibration, interface intelligibility, and teacher capacity to interpret and act upon the evidence presented. In other words, educational utility emerged from the interaction between algorithmic inference and pedagogical mediation (VIGENTINI *et al.*, 2017).

REMUNOM
ISSN 2178-6925

Received: 10/02/2026 **– Accepted:** 21/03/2026
Vol: 13.03
DOI: 10.66104/fkfg6q38
Pages: 1-25

6.2. Trade-offs: personalization versus privacy and automation versus teacher autonomy

The results also reinforce the existence of structural trade-offs in AI-supported education. Personalization requires data collection, behavioral monitoring, and integration of heterogeneous evidence, which increases risks related to surveillance, misuse of personal data, and asymmetries in visibility among students. Even when the model is technically effective, its legitimacy depends on transparent purpose specification, data minimization, role-based access control, and the possibility of audit and contestation (MESSAOUDI, 2024).

A second trade-off concerns automation and teacher autonomy. While the model reduced operational workload and accelerated instructional diagnosis, excessive dependence on alerts and rankings may gradually shift pedagogical agency from teachers to the system. This risk is especially relevant in dynamic and heterogeneous educational settings, where behavioral traces do not fully capture contextual, socio-emotional, and curricular dimensions of learning. For this reason, the human-in-the-loop structure should be understood not as an accessory feature, but as a core pedagogical Safeguard (ROJAS-SÁNCHEZ, 2024).

6.3. Comparison with related studies

Compared with existing educational systems, the proposed model differs in the degree of integration between prediction, recommendation, explainability, pedagogical control, and governance. Native LMS analytics typically provide descriptive dashboards and raw indicators, but they often lack predictive prioritization and limited capacity for instructional orchestration. Rule-based early warning systems, in turn, are more interpretable but less sensitive to nuanced behavioral patterns and temporal variation. Conventional recommenders may retrieve relevant content, yet they frequently operate with limited pedagogical alignment and weak governance mechanisms.

In contrast, the present model integrates predictive estimation, behavior-aware ranking, teacher-defined instructional constraints, and approval-based intervention. Thus, its originality lies less in any isolated component and more in the articulation of these elements within a dynamic instructional workflow. This distinction is important because many existing systems support either personalization, analytics, or

REMUNOM
ISSN 2178-6925
Received: 10/02/2026 **– Accepted:** 21/03/2026
Vol: 13.03
DOI: 10.66104/fkfg6q38
Pages: 1-25

feedback, whereas the proposed artifact explicitly combines these dimensions while preserving teacher agency and auditability (JAIN; MENON, 2023).

6.4. Limitations of the study

Despite the positive results, the study has important limitations. First, the empirical validation was conducted in a single institution and a restricted disciplinary context (STEM fields), which constrains external validity and generalizability. Second, the model remains dependent on the quality and density of LMS logs; sparse interaction records, missing data, or inconsistent instructional practices may reduce predictive stability and recommendation relevance.

Third, even though subgroup auditing and mitigation procedures were implemented, residual biases may persist, especially in contexts marked by unequal access, heterogeneous digital participation, or underrepresented student profiles. Fourth, the model captures behavioral proxies of learning rather than learning itself. As such, it may miss dimensions related to motivation, conceptual understanding, socio-emotional barriers, and off-platform study strategies. Fifth, the duration of the intervention, although sufficient for quasi-experimental comparison, may still be insufficient to demonstrate sustained long-term effects across semesters and curricular transitions (SAYARI, 2024).

These limitations reinforce the argument that AI in education should not be evaluated exclusively through accuracy metrics. Longitudinal validation, multi-institutional replication, stronger causal designs, and continuous fairness auditing remain necessary for consolidating the proposed model as a robust and transferable contribution.

7. Conclusions and future research

7.1. Summary of contributions

This article presented, implemented, and empirically evaluated an AI model designed to support teaching in dynamic educational environments. The study contributes by integrating dynamic learning profiles, supervised prediction of risk and mastery, hybrid pedagogical recommendation, rubric-based feedback support, and a governance-oriented human-in-the-loop layer within a single socio-technical

REMUNOM
ISSN 2178-6925

Received: 10/02/2026 – **Accepted:** 21/03/2026
Vol: 13.03
DOI: 10.66104/fkfg6q38
Pages: 1-25

architecture. In addition to describing the artifact, the study reported empirical results regarding technical performance, pedagogical impact, subgroup fairness, and operational feasibility in a hybrid higher education context. The contributions can be summarized in three areas (Table 1):

Table 1: Contributions

Front	Contribution	Objective Summary
Theoretical	Design requirements for educational AI in dynamic environments	Systematizes the principles of dynamism, diversity, and inclusion as design requirements, integrating learning analytics with teacher support
Methodological	Technical and pedagogical evaluation design	Proposes an integrated assessment of algorithmic performance and pedagogical impact, recognizing the dependence on data quality and the need for XAI/visualization for teaching decisions
Applied	Operational architecture of the socio-technical cycle	Defines an architecture that operationalizes “data → inference → intervention → monitoring,” with dashboards and mechanisms for timely intervention.

Source: authors.

7.2. Recommendations for adoption in institutions

For institutional adoption, the following is recommended (Table 2):

Table 2: Recommendations

Number	Recommendation	Practical Guidelines	Purpose/Mitigated Risk
1	Data governance from the outset	Consent, data minimization, access control, auditing, and anonymization/pseudonymization	Reduces risks related to monitoring, misuse, and non-compliance
2	Infrastructure and operational sustainability	Connectivity diagnostics, devices, technical support, and operational/maintenance capabilities	Prevents the exacerbation of inequalities and operational failures
3	Gradual adoption	Start with high-value, low-risk cases before moving on to critical automations	Minimizes the risk of negative impact and increases acceptance
4	Faculty training and co-design	Teachers participate in the calibration of rules/policies and validation of feedback	Preserves faculty autonomy and reduces resistance
5	Integration with the existing ecosystem	Prioritize interoperability and usability (connectors, workflows, UX)	Preserves faculty autonomy and reduces resistance

Source: authors.

7.3. Upcoming events

As a natural continuation of this work, the following is proposed (Table 3):

Table 3: Recommendations

Future Direction	Objective	Implementation Guidelines	Safeguards/Notes
Data expansion and diversification	Expand the model’s reach and coverage	New courses; privacy-preserving strategies and governance	Data minimization, explicit purpose, and access controls
Longitudinal and multi-institutional validation	Verify sustained effects	Semester-by-semester monitoring and replication in different contexts	Account for seasonal and institutional variables

REMUNOM
ISSN 2178-6925

Received: 10/02/2026 **– Accepted:** 21/03/2026
Vol: 13.03
DOI: 10.66104/fkfg6q38
Pages: 1-25

Multimodality with safeguards	Investigate additional indicators as needed	Voice/expressions only with pedagogical justification and consent	Prevent surveillance and reduce the risk of intrusion and abuse
Improved explainability and pedagogical control	Make decisions understandable and adjustable	Teacher-oriented XAI and policy adjustments	Transparency, auditability, and support for decision-making
Continuous monitoring of equity	Reduce algorithmic bias	Metrics by subgroups, periodic audits, and active mitigation	Require representative data and fairness governance
Interoperability and user-centered design	Increase sustainable adoption	Evolving connectors/UX, adherence to the living curriculum, and teaching routines	Reduces friction, improves perceived utility, and encourages repeat use

Source: authors.

References

AGUILAR YUSTE, M.; ROJAS-SÁNCHEZ, E. The Teacher and his or her role in the use of Artificial Intelligence: the conflict of AI in the Educational System. *International Journal of Research Publications*, v. 154, n. 1, 2024. DOI: 10.47119/ijrp1001541820247037. Available at: https://doi.org/10.47119/ijrp1001541820247037.

AKBAR, K. F. et al. Inclusive Education Practices: Fostering an Accessible Learning Environment for Diverse Learners, 2023. DOI: 10.59613/global.v1i3.35. Available at: https://doi.org/10.59613/global.v1i3.35.

APETORGBOR, M. et al. Leveraging Artificial Intelligence for Effective Assessment and Evaluation in Education: A Comprehensive Review. [S.l.]: IEEE, 2024. p. 1–6. DOI: 10.1109/idicaiei61867.2024.10842940. Available at: https://doi.org/10.1109/idicaiei61867.2024.10842940.

ARMAS, L. Inteligencia artificial en la educación: personalización del aprendizaje y adaptación educativa. *CID – Centro de Investigación y Desarrollo*, 2023. DOI: 10.37811/cli_w965-41. Available at: https://doi.org/10.37811/cli_w965-41.

BAETA, P.; PEDRO, N. Innovative Educational Environments vs Regular Classrooms: Analysis of pedagogical dynamics and learning activities. In: *IBERIAN CONFERENCE ON INFORMATION SYSTEMS AND TECHNOLOGIES (CISTI)*, 2019. [S.l.]: IEEE, 2019. DOI: 10.23919/CISTI.2019.8760765. Available at: https://doi.org/10.23919/CISTI.2019.8760765.

BAYAGA, A. Leveraging AI-enhanced and emerging technologies for pedagogical innovations in higher education. *Education and Information Technologies*, 2024. DOI: 10.1007/s10639-024-13122-y. Available at: https://doi.org/10.1007/s10639-024-13122-y.

CASALINO, G. et al. Incremental and Interpretable Learning Analytics Through Fuzzy Hoeffding Decision Trees. In: [S.l.]: Springer, 2023. p. 674–690. DOI: 10.1007/978-3-031-29800-4_51. Available at: https://doi.org/10.1007/978-3-031-29800-4_51.

CORTEZ, J. L. Tecnologías emergentes en la educación del siglo XXI. *MCJ*, v. 1, n. 4, p. 40–55, 2023. DOI: 10.70881/mcj/v1/n4/25. Available at: https://doi.org/10.70881/mcj/v1/n4/25.

DA SILVA, L. C. A. et al. Active methodologies and digital technologies in learning: A systematic literature review. In: *IBERIAN CONFERENCE ON INFORMATION SYSTEMS AND TECHNOLOGIES (CISTI)*, 2022. [S.l.]: IEEE, 2022. p. 1–5. DOI: 10.23919/cisti54924.2022.9820582. Available at: https://doi.org/10.23919/cisti54924.2022.9820582.

REMUNOM
ISSN 2178-6925

Received: 10/02/2026 **– Accepted:** 21/03/2026
Vol: 13.03
DOI: 10.66104/fkfg6q38
Pages: 1-25

DWI, M.; HIDAYATULLAH, A. N. A. Machine Learning in Multicultural Education. *Pakistan Journal of Life and Social Sciences*, v. 22, n. 1, 2024. DOI: 10.57239/pjlss-2024-22.1.0084. Available at: https://doi.org/10.57239/pjlss-2024-22.1.0084.

EMBARAK, O. Towards an Adaptive Education through a Machine Learning Recommendation System. In: *INTERNATIONAL CONFERENCE ON ARTIFICIAL INTELLIGENCE*, 2021. [S.l.]: IEEE, 2021. p. 187–192. DOI: 10.1109/ICAIIC51459.2021.9415211. Available at: https://doi.org/10.1109/ICAIIC51459.2021.9415211.

IGNJATOVIĆ, G. AI technologies in education: Regulatory frameworks at the international, regional, and national level. *Zbornik Radova Pravnog Fakulteta u Nišu*, v. 63, n. 103, p. 235–260, 2024. DOI: 10.5937/zrpfn1-55374. Available at: https://doi.org/10.5937/zrpfn1-55374.

IMAN, M. Z.; ASIS, A. A.; RAHMA, A. U. Z. Enhancing Personalized Learning: The Impact of Artificial Intelligence in Education. *Edu Spectrum*, v. 1, n. 2, p. 101–112, 2024. DOI: 10.70063/eduspectrum.v1i2.55. Available at: https://doi.org/10.70063/eduspectrum.v1i2.55.

JAIN, L. R.; MENON, V. AI Algorithmic Bias: Understanding its Causes, Ethical and Social Implications. In: *ICTAI*, 2023. [S.l.]: IEEE, 2023. p. 460–467. DOI: 10.1109/ictai59109.2023.00073. Available at: https://doi.org/10.1109/ictai59109.2023.00073.

JOSE, D. Data Privacy and Security Concerns in AI-Integrated Educational Platforms. *RMC*, v. 5, n. 2, p. 87–91, 2024. DOI: 10.46632/rmc/5/2/19. Available at: https://doi.org/10.46632/rmc/5/2/19.

KALYUGA, S. Rapid Dynamic Assessment for Learning. In: [S.l.]: Springer Netherlands, 2012. p. 43–60. DOI: 10.1007/978-94-007-4507-0_3. Available at: https://doi.org/10.1007/978-94-007-4507-0_3.

KHAN, M. I. Role of AI in Enhancing Accessibility for People with Disabilities. *Deleted Journal*, v. 3, n. 1, p. 281–291, 2024. DOI: 10.60087/jaigs.v3i1.120. Available at: https://doi.org/10.60087/jaigs.v3i1.120.

KHAZANCHI, P.; KHAZANCHI, R. Pedagogical Practices in Teaching Students With Disabilities in Inclusive Education. In: [S.l.]: IGI Global, 2021. p. 66–86. DOI: 10.4018/978-1-7998-7630-4.CH004. Available at: https://doi.org/10.4018/978-1-7998-7630-4.CH004.

KONADE, S. et al. Implementation of an Automated Answer Evaluation System. [S.l.]: IEEE, 2024. p. 457–462. DOI: 10.1109/ic2pct60090.2024.10486693. Available at: https://doi.org/10.1109/ic2pct60090.2024.10486693.

KUMAR, A. et al. A Comprehensive Survey on AI in Learning Management System. *Preprints*, 2025. DOI: 10.20944/preprints202501.0697.v1. Available at: https://doi.org/10.20944/preprints202501.0697.v1.

LEONG, W. Y.; LEONG, Y. Z.; LEONG, W. S. Artificial Intelligence in education. *IET Conference Proceedings*, v. 2024, n. 22, p. 183–184, 2025. DOI: 10.1049/icp.2024.4341. Available at: https://doi.org/10.1049/icp.2024.4341.

LIU, L. Research on Personalized Education Recommendation Algorithm Based on Artificial Intelligence. [S.l.]: IEEE, 2023. p. 531–535. DOI: 10.1109/icapc61546.2023.00104. Available at: https://doi.org/10.1109/icapc61546.2023.00104.

MAROUF, M. et al. AI in Real-Time Student Performance Monitoring Using IoE. In: *Advances in Computational Intelligence and Robotics Book Series*. [S.l.]: IGI Global, 2024. p. 275–288. DOI: 10.4018/979-8-3693-7367-5.ch019. Available at: https://doi.org/10.4018/979-8-3693-7367-5.ch019.

REMUNOM
ISSN 2178-6925

Received: 10/02/2026 **– Accepted:** 21/03/2026
Vol: 13.03
DOI: 10.66104/fkfg6q38
Pages: 1-25

MESSAOUDI, A. Les défis de l'IA dans l'éducation: de la protection des données aux biais algorithmiques. *Médiations & Médiatisations*, n. 18, p. 148–160, 2024. DOI: 10.52358/mm.vi18.409. Available at: https://doi.org/10.52358/mm.vi18.409.

MORALES-CHAN, M. et al. Personalized Feedback in Massive Open Online Courses: Harnessing the Power of LangChain and OpenAI API. *Electronics*, 2024. DOI: 10.3390/electronics13101960. Available at: https://doi.org/10.3390/electronics13101960.

NODZYŃSKA-MOROŃ, M. Artificial intelligence in the teacher's work. In: [S.l.]: [s.n.], 2024. p. 29–54. DOI: 10.24917/9788368020403.3. Available at: https://doi.org/10.24917/9788368020403.3.

OTU, G. A. et al. Prediction accuracy analysis of machine learning classifiers on student course assessment methods. *Fudma Journal of Sciences*, v. 8, n. 6, p. 288–298, 2024. DOI: 10.33003/fjs-2024-0806-2927. Available at: https://doi.org/10.33003/fjs-2024-0806-2927.

PATIL, J. M.; GUPTA, S. R. Analytical Review on Various Aspects of Educational Data Mining and Learning Analytics. [S.l.]: IEEE, 2019. DOI: 10.1109/ICITAET47105.2019.9170143. Available at: https://doi.org/10.1109/ICITAET47105.2019.9170143.

REKHA, K. et al. Ai-Powered Personalized Learning System Design: Student Engagement And Performance Tracking System. [S.l.]: IEEE, 2024. p. 1125–1130. DOI: 10.1109/icacite60783.2024.10617155. Available at: https://doi.org/10.1109/icacite60783.2024.10617155.

SAYARI, K. Infrastructure, and Investment Needs for AI Implementation in Education. In: *Advances in Educational Technologies and Instructional Design Book Series*. [S.l.]: IGI Global, 2024. p. 141–162. DOI: 10.4018/979-8-3373-1017-6.ch005. Available at: https://doi.org/10.4018/979-8-3373-1017-6.ch005.

SCALISE, K.; MALCOM, C.; KAYLOR, E. A tale of two worlds: Machine learning approaches at the intersection with educational measurement. [S.l.]: OECD, 2023. DOI: 10.1787/d01eb8a4-en. Available at: https://doi.org/10.1787/d01eb8a4-en.

SCHÖNBERGER, M. et al. An AI-based lesson planning software to support competence-based learning. In: *INTERNATIONAL CONFERENCE ON HIGHER EDUCATION ADVANCES (HEAd'22)*, 2022. [S.l.]: [s.n.], 2022. DOI: 10.4995/head22.2022.14599. Available at: https://doi.org/10.4995/head22.2022.14599.

SEPTIANI, R. A.; RAMADANI, A. N. AI: Apakah Guru Masih Punya Peran di Masa Depan. *Inspirasi Dunia*, v. 4, n. 1, p. 263–272, 2025. DOI: 10.58192/insdun.v4i1.2947. Available at: https://doi.org/10.58192/insdun.v4i1.2947.

SHIELDS, J. A. E. Classroom assessment. In: [S.l.]: Elsevier, 2023. p. 519–528. DOI: 10.1016/b978-0-12-818630-5.10064-8. Available at: https://doi.org/10.1016/b978-0-12-818630-5.10064-8.

SILVA, A. de O.; JANES, D. dos S. Editorial: Artificial Intelligence in Education – Navigating Ethical, Legal, and Technological Frontiers. *Review of Artificial Intelligence in Education*, v. 4, n. 00, e034, 2023. DOI: 10.37497/rev.artif.intell.educ.v4i00.34. Available at: https://doi.org/10.37497/rev.artif.intell.educ.v4i00.34.

SONG, X. et al. A Comprehensive Guide to Explainable AI: From Classical Models to LLMs, 2024. DOI: 10.31219/osf.io/wbk36. Available at: https://doi.org/10.31219/osf.io/wbk36.

TANG, K. H. D. Implications of Artificial Intelligence for Teaching and Learning. *Acta Pedagogia Asiana*, v. 3, n. 2, p. 65–79, 2024. DOI: 10.53623/apga.v3i2.404. Available at: https://doi.org/10.53623/apga.v3i2.404.

REMUNOM
ISSN 2178-6925

Received: 10/02/2026 **– Accepted:** 21/03/2026
Vol: 13.03
DOI: 10.66104/fkfg6q38
Pages: 1-25

TAUFIKIN, M. S. I. et al. The Impact of AI on Teacher Roles and Pedagogy in the 21st Century Classroom. [S.l.]: IEEE, 2024. p. 1–5. DOI: 10.1109/ickecs61492.2024.10617236. Available at: https://doi.org/10.1109/ickecs61492.2024.10617236.

TRIVEDI, N. B. AI in Education – A Transformative Force. [S.l.]: IEEE, 2023. p. 1–4. DOI: 10.1109/idicaiei58380.2023.10406541. Available at: https://doi.org/10.1109/idicaiei58380.2023.10406541.

VIGENTINI, L. et al. Overcoming the MOOC Data Deluge with Learning Analytic Dashboards. In: [S.l.]: Springer, 2017. p. 171–198. DOI: 10.1007/978-3-319-52977-6_6. Available at: https://doi.org/10.1007/978-3-319-52977-6_6.

ZHANG, J.; KAMSIN, A. Personalized learning model based on machine learning algorithms. *International Journal of Informatics and Communication Technology*, v. 13, n. 3, p. 470–475, 2024. DOI: 10.11591/ijict.v13i3.pp470-475. Available at: https://doi.org/10.11591/ijict.v13i3.pp470-475.