Modeling an AI-driven adaptive learning platform for students with special educational needs

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Abstract

This paper is devoted to a formalized approach to modeling an AI-driven adaptive learning platform specifically designed for students with special educational needs. The developed platform integrates generative artificial intelligence, reinforcement learning algorithms to dynamically personalize educational trajectories. The model leverages psychophysiological diagnostic data, contextual parameters, and real-time performance feedback to continuously adapt instructional content and methodologies. This research demonstrates the potential of integrating adaptive learning methodologies with generative AI, marking a significant advancement in personalized education systems and offering valuable implications for inclusive educational and AI-driven applications.

Keywords

Adaptive learning, generative AI models, special educational needs.

1. Introduction

The need for equitable, high-quality education has spurred the rise of digital platforms that use generative AI to create, personalize, and refine learning experiences. This technological shift aligns with global initiatives to promote social inclusion and to comply with international standards on accessibility and equal rights in education [1, 2]. The exigency of addressing diverse learners requirements – spanning cognitive and sensory supports to highly adaptive instructional methodologies – drives the need for robust, meticulously modeled information systems. Such systems must merge pedagogical frameworks, real-time data-driven adaptation algorithms, and universal-design principles to construct flexible, learner-centred digital ecosystems [3, 4].

From a systems-engineering perspective, designing an educational platform for learners with special educational needs involves managing multiple layers of complexity. Equally, the intangible facets of user interaction require precise calibration of cognitive load, individualized navigation flows, and real-time adaptation of multimodal content.

These demands necessitate sophisticated architectural modelling – incorporating micro-service orchestration and privacy-preserving analytics – to mitigate risks of performance bottlenecks, data breaches, or diminished learner engagement [5].

Personalized instructional materials – such as speech-recognition transcriptions, text-to-speech renderings, sign-language avatars, and alternative input modalities – must be seamlessly integrated through modular interfaces that support future feature extensions. Large-scale machine-learning models further enhance the platform's capacity to tailor lessons, trigger proactive interventions, and monitor progress in real-time.

Yet this reliance on data-intensive operations obliges stringent safeguards for sensitive user profiles, including differential-privacy techniques strategies.

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2. Literature Review

The issue of implementing adaptive learning in the context of contemporary technological advancement has garnered considerable attention from scholars who have explored various dimensions of this phenomenon. Aulakh et al. [7] examined the integration of digital technologies during the COVID-19 pandemic, emphasizing the critical role of adaptability in processing extensive datasets.

Researchers at [8, 9] analyzed the potential of modern educational technologies to support individuals with mild intellectual disabilities, thereby highlighting inclusive instructional strategies.

Peng et al. [10] supported the development of smart learning environments that leverage the full potential of digital educational platforms.

The issue of learning personalization was systematically addressed by Hocine and Sehaba [11], who reviewed the functionality of personalized online education systems tailored for learners with cognitive impairments.

Hussein and Al-Chalabi [12] proposed the use of specialized pedagogical agents capable of enhancing students' experiences within adaptive learning frameworks. In the post-pandemic era, the scholarly discourse has increasingly emphasized the necessity of personalization and the continuous evolution of digital tools in education. This trajectory reflects a broader trend within modern pedagogical thought, which seeks to accommodate the specificities of learners across all educational stages. Moreover, the design and refinement of digital online learning ecosystems have emerged as a distinct field of inquiry.

Beem et al. [13], for instance, investigated the contextual application of design methodologies within African educational systems, which significantly contributed to the discourse on inclusive education.

De Medio et al. [14] explored the capabilities of the Moodle platform in structuring courses for inclusive pedagogy.

Empirical studies by Hubalovsky et al. [15] demonstrated the efficacy of adaptive online learning environments in equipping secondary school students with essential competencies.

Labonté and Smith [16] conducted a comparative empirical analysis, highlighting the advantages of adaptive digital learning in secondary education, particularly in inclusive settings.

Conversely, Khamparia et al [17] illuminated persistent challenges associated with digital educational environments; although their study predates recent advancements, the issues they identified remain pertinent today.

Efforts to address these limitations were undertaken by Persico et al. [18], who adapted the technology acceptance model to uncover determinants that hinder the diffusion of emerging technologies in inclusive education.

Pratama [19] further developed hypotheses around the adoption of such technologies, using Google Classroom as a case study.

Eljak et al. [20] carried out a systematic review exploring the potential applications of cloud computing technologies within e-learning platforms. The adoption of diverse learning management systems serves as a cornerstone for cultivating an inclusive e-learning environment.

Platforms such as Moodle, Canvas, and Google Classroom offer a wide array of functionalities that enable the personalization of educational pathways by tailoring assignments to learners' specific needs, generating adaptive assessments, and delivering prompt feedback.

Equally critical are adaptive learning solutions – examples include Knewton, DreamBox, and Smart Sparrow – which rapidly evaluate student responses and dynamically adjust subsequent tasks to match their demonstrated knowledge level or particular requirements. Interactive learning tools further enhance inclusivity by facilitating the creation of engaging, multimedia-rich instructional content, though their effectiveness hinges on instructors' ability to calibrate difficulty appropriately. Moreover, sustaining robust communication channels – through virtual classrooms, online discussion forums, and one-on-one consultations – is indispensable to ensuring social presence and fostering a supportive educational climate; without sufficient opportunities for meaningful interaction, the efficacy of an e-learning platform is fundamentally undermined.

Assistive learning technologies have become vital for ensuring an inclusive e-learning environment.

Tools such as Read&Write support students with reading, writing, and learning difficulties by offering text-to-speech capabilities, built-in dictionaries, and translation features.

Likewise, Kurzweil 3000 aids learners with dyslexia or other reading challenges, providing high-quality speech synthesis alongside text highlighting, annotation, and resource-management functions.

Dragon NaturallySpeaking leverages advanced speech recognition to let users dictate content and control their computers via voice commands [21]. For students with visual impairments, screen readers like JAWS, NVDA, and VoiceOver convert on-screen text to spoken word, whereas learners with hearing impairments can use audio-amplification software or live captioning. Although these studies provide a generalized foundation, they fall short in addressing the requirements of education, especially concerning the reconfiguration of digital technologies. This gap underscores the necessity of systematizing the instruments that facilitate adaptive learning, a challenge to which the study aspires to respond.

3. Formal Problem Statement

To model the recommendation system within an inclusive learning platform for students with special educational needs, we introduce the following fundamental sets and data spaces:

1. Set of Participants – $P=\{p_1, p_2, \ldots, p_W\}$, where W is the total number of participants in the learning process.

2. Space of Initial Educational Goals – $E=\{e_{i,j,k}, i\in I, j\in J, k\in K\}$, where: i is the index of a subject domain (e.g., mathematics, arts, life skills), j is the sequential identifier or level of a specific educational goal, k indicates the modality or form of instruction (e.g., face-to-face, distance learning, multimedia).

3. Space of Diagnostic Data – $X=\{x_p^{(d)}, p\in P, d\in D\}$, where each d d represents a type of diagnostic test – psychophysiological or cognitive. This space captures student evaluations that inform system about individual learning needs.

4. Space of Personalized Requirements – $\psi: X \rightarrow P(R)$, where ψ is a function that maps diagnostic data in X to a set of personalized requirements $P(R)$. In other words, for each participant $p \in P$, ψ produces a specific set of educational accommodations and supports (e.g., assistive technology).

5. Space of Contextual Parameters – $C=\{c_p, p\in P\}$, which includes environmental factors, instructor characteristics, and social-psychological contexts. For instance, c_p may describe whether learning is happening at home or in a resource room, as well as any relevant psycho-emotional conditions.

6. Space of Dynamic Feedback Data – $D=\{d_p(t), p\in P, t\in T\}$, where t is a time parameter, and $d_p(t)$ represents the current learning outcomes or performance metrics for participant p at time t. These data inform continuous adjustments of the platform's recommendations.

7. Set of AI-Agent Functional Capabilities – $A=\{a_1, a_2, ,, .a_{n_A}\}$, where each a_i is an adaptive learning algorithm or personalized feedback service provided by the AI assistant. This includes capabilities such as real-time curriculum adaptation, automated generation of simplified content, and assistive media synthesis (e.g., visual or auditory supports based on learner preference). Notably, we deploy a generative transformer-based model, similar in architecture to GPT-4.

Each participant $p\in P$ begins with an initial subset of educational goals $e_p \subset E$, which must be aligned to the $c_p \in C$. We introduce a context-adaptation function:

$$\chi: E \times C \rightarrow E', \tag{1}$$

where E' is the refined set of educational goals, adapted to the specific conditions of the learning environment and individual student characteristics.

Drawing on the adapted goals, personal requirements, and the feedback data, we define the support module m_p for participant p at time t through:

$$m_p = f\left(X\left(e_p, c_p\right), \psi\left(x_p\right), A, d_p(t), t\right), \tag{2}$$

where $X\left(e_p, c_p\right)$, denotes the adapted subset of educational goals for participant p as produced by function χ; $\psi\left(x_p\right)$ yields the personalized requirements aligned to the participant's diagnostic results; A is the set of AI functionalities available to recommend or enact instructional strategies (e.g., GPT-based assistants, real-time language translation); $d_p(t)$ represents current feedback metrics on performance and learning effectiveness; t is the time parameter, enabling the model to consider recency of data and stage of the learning process.The function $f(\cdot)$ tackles a multi-criteria optimization problem: it aims to choose an optimal combination of technological tools from L and AI services from A that best match each participant's context, abilities, and goals.

Through repeated evaluation of m_p over time, the system continuously refines the learner's educational pathway – updating recommended tools, reconfiguring lesson sequences, and generating personalized interventions.

We define the system state S at time t as:

$$S(t) = \left(X, C, E', D(t)\right), \tag{3}$$

encompassing: the accumulated diagnostic information X, the contextual parameters, the adapted educational goals E', the dynamic feedback $D(t)$, capturing performance at time t. We formulate the decision process as a mapping π from the current system state $S(t)$ to an action $a \in A$. Formally, let:

$$\pi : S \rightarrow A, \tag{4}$$

At each discrete time step t, the policy π prescribes an action $a = \pi\left(S(t)\right)$ based on the observable state $S(t)$. In our application, such actions include: (1) deploying a GPT-based assistant to simplify textual materials or (2) generating high-priority alerts if learner engagement metrics drop below a defined threshold. To enable policy improvement over time, we embed this framework within a reinforcement learning paradigm. We introduce a scalar reward function,

$$R : S \times A \rightarrow R, \tag{5}$$

that assesses the immediate outcome of executing action $a \in A$ in state S. The reward may encode various performance indicators, such as test score increments, engagement levels, or psychosocial benefits. The goal is to find an optimal policy π that maximizes the expected cumulative discounted reward over possible trajectories:

$$\pi = arg \max_{\pi} E_{\tau \sim \pi}\left[\sum_{t=0}^{\infty} \gamma^t R\left(S(t), \pi\left(S(t)\right)\right)\right], \tag{6}$$

where τ represents state – action trajectories generated by following π and $\gamma \in (0,1)$ is a discount factor that reduces the impact of future rewards relative to immediate ones.

In practice, π is modeled as a parameterized generative policy network – a lightweight feedforward neural architecture with a stochastic output layer that produces distributions over actionable AI strategies, including generative content creation.

Over multiple iterations, the system converges to a policy that adaptively refines the learning experience for each individual, bridging diagnostic information and performance data to deliver *targeted interventions.* To operationalise this optimisation in practice, we treat π as a parameterised stochastic policy – typically a feed-forward network that maps the observable state vector to a probability distribution over the available AI-agent actions.

At every step platform collects a roll-out of interactions, computes the empirical return:

$$G_t = \sum_{k \geq t} \gamma^{k-t} R\left(S(k), A(k)\right), \tag{7}$$

and updates the policy parameters with a clipped policy-gradient rule.

The critic network is trained in parallel to minimise the temporal-difference error $\delta_t = G_t - V\left(S(t)\right)$, providing a low-variance baseline for the actor.

4. Results

Figure 1 shows the Use Case diagram, which delineates the spectrum of user-system interaction scenarios by formally capturing the permissible sequences of actions within the operational boundaries.

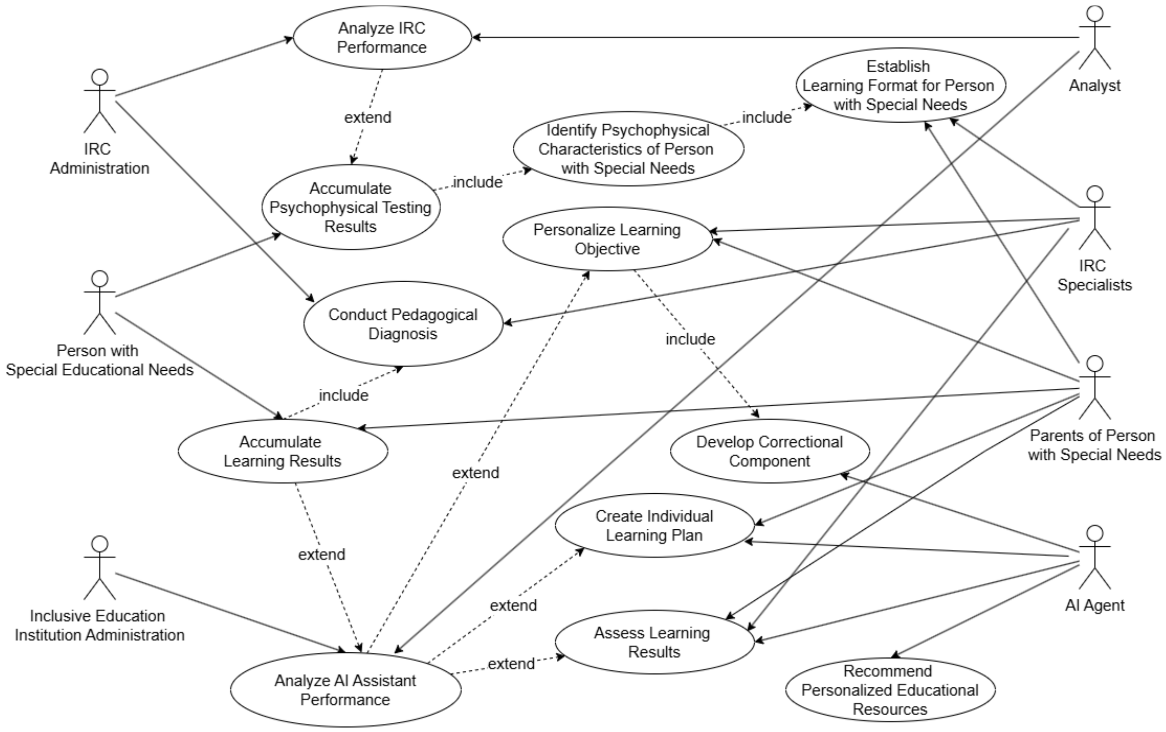

Figure 1: Use Case Diagram

The presented diagram illustrates a multifaceted interaction among various key stakeholders and processes involved in supporting a learner with special educational needs in an inclusive environment.

On one side, the analyst, the administration of the Inclusive Resource Center, and IRC specialists initiate and coordinate the analysis of psychophysiological indicators, establishing individual characteristics and an appropriate learning format. On the other side, parents and the learner with special needs collaborate with the specialists during the pedagogical diagnostics stage and the accumulation of learning outcomes. Based on the gathered data, an individualized educational plan is formed, incorporating both corrective elements and personalized educational goals.

Figure 2 shows UML Activity diagram, which traces the iterative AI-driven adaptive-learning workflow for a student with special needs – charting parallel preparatory steps, lesson-time digital support, post-lesson assessment, data aggregation, and continuous algorithm refinement within the educational ecosystem.

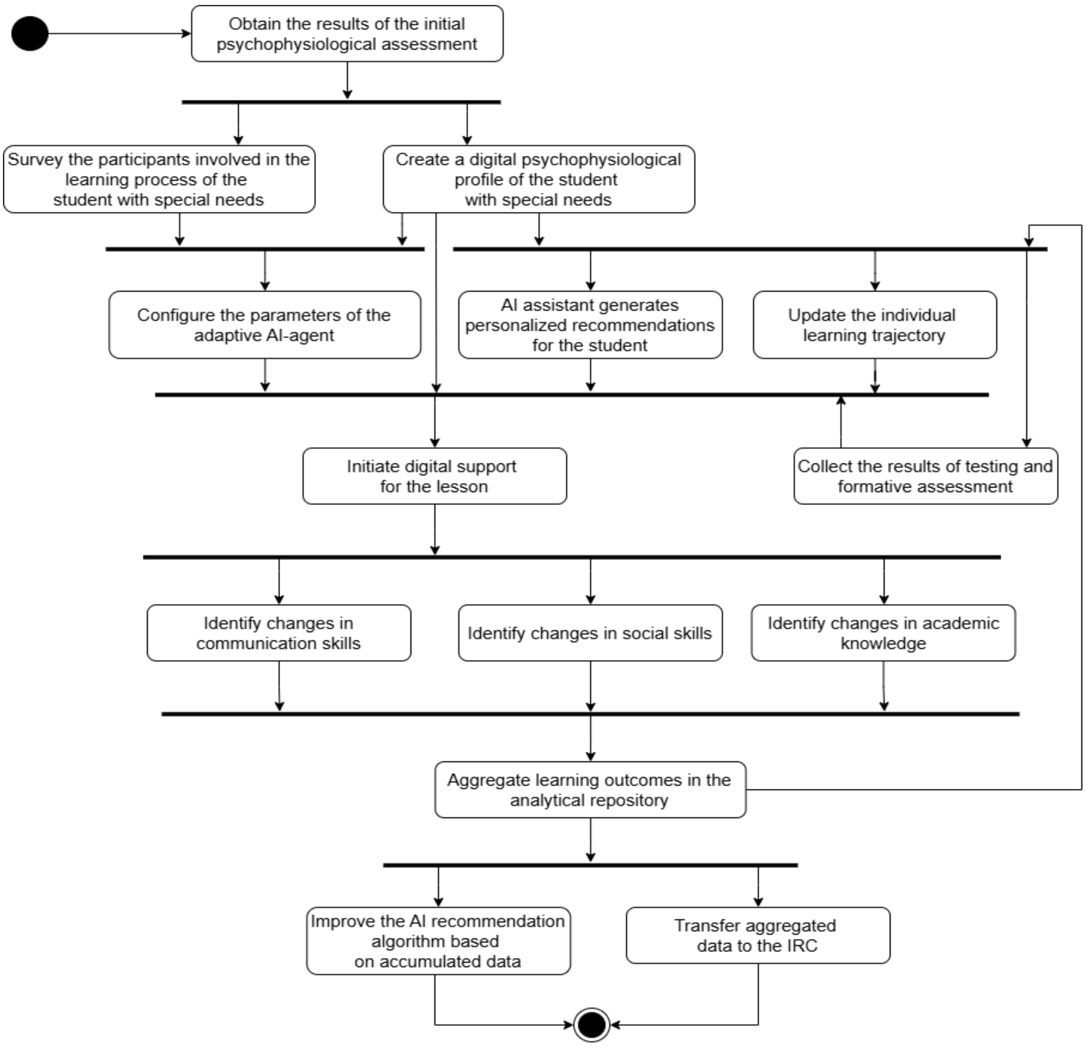

Figure 2: Structural learning model of a student with special educational needs

The cycle starts with the student's psychophysiological assessment, whose results feed two parallel tasks: stakeholder surveys and creation of a digital profile. Using both, the platform tunes an adaptive AI agent, generates first-step recommendations and updates the student's learning path.

Digital support is then activated for the lesson; test and formative-assessment data collected during the session immediately refine that path. After each lesson the system checks how communication, social and academic skills have changed and stores the findings in an analytical repository. During the analysis of the educational process for individuals with special educational needs, a series of fundamental functional stages were identified, each exhibiting features such as adherence to a rigorously structured sequence of phases and the necessity for the synchronous execution of specific educational tasks within defined stages. To formalize these requirements, the formalism of Petri nets will be used as a high-level mathematical abstraction.

Based on the formalized description of inclusive learning processes, we proceed to construct a model of the inclusive educational process using Petri nets as an analytical framework. Within this model, the net is presented as both a graphical and analytical structure, formed by finite sets of positions (P) and transitions (T), alongside corresponding IO functions. The semantics of transitions within the net encapsulate events that signify the fulfillment of specific instructional objectives, whereas places are interpreted as prerequisite conditions necessary for the occurrence of such events.

Figure 3 presents the Petri net C = (P, T, I, O), which models the learning process for individuals with special educational needs, where the set of transitions T = $\{t_{1,}t_{2,},\ldots,t_{12}\}$ and set of positions $P\{p_{1,}p_{2,},\ldots,p_{15}\}$.

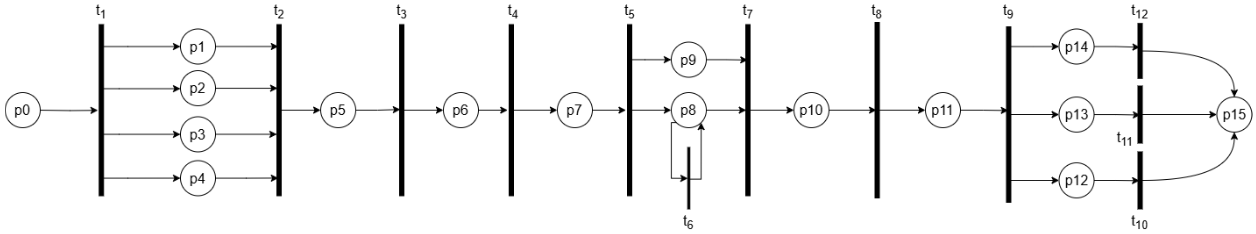

Figure 3: Petri Net as a Model of the Learning Process for Individuals with Special Educational Needs

We shall define the positions (also referred to as places) of the Petri net along with their corresponding semantic interpretations and present them systematically in Table 1. In the context of this interpretation, each position in the net represents a specific condition or state that must be fulfilled prior to the execution or occurrence of a particular event, which is modeled as a transition.

Table 1
Positions of Petri net

Position	Interpretation of the position
p_0	Necessity for the development of an AI-assisted educational complex for students with special educational needs
p_1	Identification data of the individual
p_2	Diagnostic conclusions from the psycho-medical-pedagogical consultation and expert assessments
p_3	Results of the parents' survey
p_4	Results of the individual's self-assessment
p_5	Educational and corrective objectives
p_6	Documented special educational needs
p_7	Formalized educational objective
p_8	Database of AI-platform components
p_9	Data repository of psychophysiological diagnostic results
p_{10}	Characteristics of the components of the AI-based learning complex
p_{11}	Project of the AI-assisted learning complex for students with special educational needs
p_{12}	Results of the implementation of the AI-assisted learning complex
p_{13}	Psychophysiological characteristics of the student (updated data on current state and corrective needs)
p_{14}	Academic achievement results (final grades, performance analysis)
p_{15}	Readiness for the subsequent operation of the system

Transitions within the Petri net, which by their nature represent events, are interpreted as processes. Table 2 presents the transitions of the Petri net.

Table 2
Transitions of the Petri net

Transition	Interpretation of the transition
t_1	Initiate the operation of the AI-based recommendation

	system: initial configuration and data initialization
t_2	Process of comprehensive assessment of psychophysiological development
t_3	Process of systematic analysis of the results from the comprehensive psychophysiological evaluation
t_4	Process of formulating recommendations aimed at optimizing the learning format
t_5	Initiate interaction with data repositories and databases related to students' learning outcomes and psychophysiological profiles
t_6	Develop software solutions in compliance with inclusive standards and accessibility requirements
t_7	Define the characteristics of the components of the AI-based learning complex
t_8	Integrate all characteristics and formulate recommendations for the structure of the AI-assisted learning complex
t_9	Transfer (implementation) of the AI-complex project into the real educational process
t_{10}	Analyze and update the repository of psychophysiological diagnostic data
t_{11}	Analyze and update the database of academic results
t_{12}	Analyze and update the data of the AI-based learning complex

The consolidated performance dashboard distils seven orthogonal indicators into a single comparative lens, revealing how the AI-driven adaptive platform reshapes the learning ecology relative to a conventional, accessibility-augmented LMS; all quantitative presented in Table 3.

Table 3

Consolidated performance (traditional vs AI-based) (author's research)

Operational Factor	Traditional LMS	AI-adaptive platform	Performance factor
Mean post-test score (%)	71%	80%	AI dynamically adapts content to individual knowledge gaps, optimizing comprehension and retention.
Course-completion (retention) rate	70 %	90 %	Adaptive learning pathways and continuous feedback keep students motivated and aligned with achievable goals.
Daily on-task engagement (minutes)	32	41	Personalized prompts and interactive content.
WCAG 2.1-AA compliance (% criteria met)	72 %	97%	AI systems automatically adjust UI/UX for accessibility based on user real-time needs.
Drop-out rate	12%	4%	Early risk detection and proactive support from AI agents reduce disengagement.
Content-update latency days)	14	2	AI integrates real-time

			feedback for rapid updates.
Personalisation index (0 – 1 scale)	0	0.85	AI models continuously tailor learning paths using psychometric and behavioral data, unlike static LMS flows.

Comparsion in table 3 shows that the AI-adaptive learning platform surpasses a conventional LMS on every monitored axis. Average post-test achievement rises from seventy-one to eighty percent, indicating a relative gain of roughly thirteen percent in overall mastery. Completion improves even more sharply, with nine learners in ten finishing the course versus seven in ten under the traditional system, a twenty-percentage-point uplift that directly reduces wasted enrolments. Day-to-day engagement deepens as well: students spend forty-one minutes per day actively working in the adaptive environment, nine minutes – or about twenty-eight percent – longer than their peers on the legacy platform, a signal of heightened motivation and sustained attention. Finally, the personalisation index jumps from zero to 0.85, confirming that more than four out of five learning sessions are now automatically tailored to each student's profile.

To quantify how real-time personalisation drive final achievement on the AI-based platform, an multiple-linear-regression model was estimated:

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \varepsilon_i, \tag{8}$$

where Y_i – post-intervention test score of learner i, X_{1i} – pre-intervention score (percentage), X_{2i} – AI-adaptability index recorded for the learner (0 – 1), X_{3i} – average daily on-task engagement (minutes), ε_i – random error term.

Multiple-linear-regression results for post-intervention performance are presented in Table 4.

Table 4
Multiple-linear-regression results for post-intervention performance

Predictor Variable	Coefficient	Standard Error	t-value	p-value
Intercept (β_0)	9.80	1.96	5.00	< 0.001
Pre-test score (β_1)	0.62	0.07	8.86	< 0.001
AI-adaptability (β_2)	11.5	3.1	3.71	< 0.001
Engagement minutes (β_3)	0.21	0.08	2.63	0.009

The regression results show that every additional percentage point earned on the pre-test is associated with a 0.62-point rise on the post-test, confirming prior knowledge as a basic driver of later success, yet the dominant influence comes from adaptive personalisation: moving the AI-adaptability index from 0 to 1 predicts an average gain of 11.5 – by far the largest single effect in the model.

5. Conclusions

In conclusion, this study demonstrates that the development of an inclusive educational information system powered by an integrated AI assistant represents a critical advancement toward ensuring equitable access to high-quality education for learners with special educational needs.

The proposed framework systematically merges regulatory compliance, adaptive pedagogical methodologies, and state-of-the-art technological components – including generative AI, reinforcement learning, cloud-based infrastructure, and privacy-preserving analytics. The formal model articulates how personalized educational pathways can be dynamically generated and continuously refined through diagnostic data, contextual adaptation, and real-time performance feedback. By embedding this logic within a reinforcement learning paradigm, the system not only responds to immediate learner needs but evolves intelligently over time, aligning instructional strategies with individual variables.

In result, this work offers a scalable and resilient blueprint for future digital learning ecosystems that aspire to combine inclusivity and personalization.

Declaration on Generative AI

During the preparation of this work, the authors used GPT-4 in order to perform grammar and spelling checks. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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