European International Journal of Pedagogics (ISSN: 2751-000X)

Received: 28 December 2025 | Accepted: 18 January 2026 | Published: 24 February 2026

DOI: 10.55640/eijp-06-02-23

RESEARCH ARTICLE

Development and Implementation of An Adaptive Learning Platform Based on Artificial Intelligence Technology

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VOLUME: Vol.06 Issue02 2026

PAGE: 96-102

Abstract

This article presents the development and implementation process of the Adaptive Digital Didactic–Content Remediation System (ADD–CRS), built on artificial intelligence (AI) technology. The purpose of the research is to identify knowledge gaps in digital learning, adaptively remediate them, and ensure transparency in the teaching process. The ADD–CRS system was designed based on a two-stage adaptive retraining methodology, aimed at reducing cognitive load and enhancing learning efficiency. Additionally, the system enables teachers to automatically generate and analyze tests and assignments linked to specific source locations. Future research is planned to focus on automated task assessment, integration with electronic gradebooks, and full automation of formative, midterm, and final assessment processes.

KEYWORDS

Adaptive learning; Artificial Intelligence (AI); Generative AI; Cognitive Load Theory; Knowledge gap remediation; Traceability; Didactic competence; LMS; GPT-4o.

INTRODUCTION

In the modern education system, the processes of digital transformation are rapidly advancing, requiring new approaches to managing learning content and assessing students' achievement levels. Although traditional Learning Management Systems (LMS) effectively perform basic administrative and instructional functions, they are mostly limited to delivering educational materials and administering standard assessments [1][2]. However, these systems face significant challenges in identifying individual students' knowledge gaps, conducting in-depth analysis, and optimizing cognitive load to build personalized learning trajectories.

Today, the integration of Artificial Intelligence (AI) and generative models (such as GPT-4o) into the educational process provides unprecedented opportunities to address these challenges [3]. Nevertheless, one of the key issues in applying AI in education remains ensuring content transparency (traceability) and maintaining source-based reliability of generated materials [4].

Most existing adaptive learning systems respond to students' incorrect answers by merely repeating the general topic or redirecting them to supplementary resources [5]. However, such systems fail to address two critical issues:

1. Analysis of precise content location: Current AI solutions can extract key concepts from PDFs, videos, or presentation slides (PPTX), yet they cannot link the identified knowledge gap to its exact source location (e.g., page number, slide, or timestamp). As a result, students are often forced to review large portions of material, which increases their cognitive load.

2. Step-wise adaptive retraining mechanism: Most systems employ either immediate deep remediation or generic

shallow recommendations when addressing knowledge gaps. This approach is not always effective. There is no mechanism that considers the learner's cognitive state — first guiding them to a low-load recommendation (precise source reference), followed by a high-load explanation (personalized deep feedback) when needed.

The main objective of this study is to develop and experimentally validate a new-generation platform — the Adaptive Digital Didactic–Content Remediation System (ADD–CRS) — based on AI technologies that can analyze educational content according to its traceable source location and implement a two-stage adaptive retraining mechanism.

The research aims to answer the following questions:

1. Can an AI-based methodology be developed to analyze multi-format educational content (PDF, video, PPTX) according to its exact source location?

2. Does the proposed two-stage adaptive retraining mechanism (initial source guidance followed by deep explanation) improve students' learning efficiency compared to traditional methods?

The scientific novelty of the ADD–CRS lies in three key innovative features:

1. Traceable Knowledge Extraction: Using GPT-4o-based AI, each extracted concept from a PDF or video is linked to its exact position in the source (e.g., [MM:SS] timestamp or Page N).

2. Source-Based Generative Assessment: The system generates test questions strictly within the selected source, ensuring that each question is explicitly linked to its source location. This enhances assessment transparency and reliability.

3. Step-Wise Adaptive Remediation: When a student gives an incorrect answer:

- In the first stage, the system provides low cognitive load remediation by directing the learner to the specific source point.
- In the second stage, if the error persists, it delivers a personalized deep explanation generated by AI.

This approach represents a new stage in the methodology of AI-enhanced digital education, enabling personalized learning, rapid identification of knowledge gaps, and their efficient remediation.

METHODS

This study was conducted using the Design-Based Research (DBR) methodology [6], which enables the systematic design, implementation, and iterative refinement of educational innovations within authentic learning environments.

The primary objective of the research was to develop and experimentally validate the effectiveness of a next-generation educational platform entitled the Adaptive Digital Didactic – Content Remediation System (ADD–CRS). This system is designed to efficiently identify and address students' knowledge gaps through adaptive digital mechanisms.

The advantage of applying the DBR approach lies in its ability to integrate theoretical model development with practical experimentation, allowing for continuous model improvement through iterative design cycles [7].

The ADD–CRS platform was developed based on a modular, non-monolithic three-tier architecture, comprising the following core components:

- Backend (Server Layer): Implemented in Python using the Django and Django REST Framework, the backend layer manages data operations through PostgreSQL and ensures seamless integration with Artificial Intelligence (AI) modules [8].
- Frontend (Client Layer): Developed using the Vue.js framework, this layer provides an interactive user interface and ensures the visual presentation of data retrieved via RESTful APIs [9].
- Artificial Intelligence Layer: Responsible for executing the key AI operations of the platform—namely content analysis, content generation, and adaptive remediation logic. This component functions through the GPT-4o model integrated via the OpenAI API [10].

The AI-driven mechanisms within the platform operate through three interrelated stages, ensuring a seamless integration between data extraction, content understanding, and adaptive assessment.

1. Traceable Content Analysis

This module links every instructional concept within the learning materials to its precise source location, thereby ensuring traceability and transparency in the learning process.

- Data Extraction: The platform automatically extracts textual content from PDF, DOCX, and PPTX files, as well as from YouTube videos and other multimedia learning resources. For video materials, transcription is carried out using the YouTube Transcript API provided by OpenAI.

- Source Location Tagging: Each extracted text segment is stored in JSON format, including metadata such as the file type and its exact position (e.g., page N, slide N, or [MM:SS] timestamp).
- Concept Identification: The structured text is sent to the GPT-4o model through the call_openai_for_content_analysis function, which identifies the core educational concepts and returns them mapped to their corresponding source locations.
- Data Storage: The resulting data are stored within the database using the Resource.processed_content_data (JSONField) and Resource.concepts (ManyToManyField) models, ensuring both traceability and interoperability.

2. Source-Based Generative Assessment

This module performs AI-driven test generation exclusively based on the selected learning resources, ensuring alignment between assessment items and instructional content.

- Prompt Restriction: In the generate_ai_test() function, a strict prompt constraint is defined for the GPT-4o model, requiring that all generated test questions must rely solely on the content of the designated resource.
- Metadata Integration: Each generated question includes source metadata such as page number, slide number, or timestamp, which are recorded in the source_location field.
- Assessment Model: All generated test items are stored in the TestQuestion model, where each question maintains consistent linkage to its source_resource and source_location attributes. This structure ensures full traceability and content-based assessment validation.

The system implements a two-stage adaptive remediation mechanism designed to address learners' knowledge gaps based on their test performance. This approach integrates cognitive load theory with adaptive learning principles to ensure both efficiency and depth in learning recovery.

- Stage 1: Shallow Remediation (Low Cognitive Load). When a student fails the initial assessment attempt, the system does not provide complex explanations. Instead, it automatically redirects the learner to the corresponding source segment identified through the source_location parameter.

Objective: To foster self-directed exploration and reflective learning by encouraging the student to independently revisit and analyze the relevant material.

- Stage 2: Deep Remediation (High Cognitive Load). If the learner fails the second attempt, the AI module initiates a personalized remediation process. Based on the error analysis, the system generates individualized explanations, provides the correct answers with conceptual justifications, and supplements them with practical examples.

Objective: To promote deep conceptual understanding and close complex knowledge gaps through targeted cognitive engagement.

All generated recommendations are stored within the AIRecommendation model and presented to the user in an adaptive and personalized format, enabling continuous learning optimization and performance tracking.

3. Data Collection and Analysis

During the empirical phase of the study, the ARD-KRT platform served as the primary source of research data. All learner interactions, performance outcomes, and AI-generated feedback were systematically recorded and analyzed to evaluate the platform's pedagogical effectiveness.

- Performance Data: Each test attempt was automatically logged, including the obtained score (StudentTestAttempt.score) and pass/fail status (is_passed). Individual responses to each question were also stored in the StudentAnswer model.
- Progress Metrics: Learners' overall achievement and engagement levels were tracked through the StudentProgress model, which recorded metrics such as lecture view duration, independent study duration, and other activity-based indicators of learning behavior.
- AI Recommendations: Personalized feedback generated by the AI module was classified according to its type and remediation stage (Stage 1 – Shallow Remediation / Stage 2 – Deep Remediation), as stored in the AIRecommendation model.

This comprehensive dataset provided the empirical foundation for subsequent statistical analysis, user activity monitoring, and evaluation of the platform's instructional effectiveness.

RESULTS

The empirical results of the study focused on evaluating both the technical and methodological effectiveness of the Adaptive Digital Didactic–Content Remediation System (ARD–KRT). The findings are presented in two main parts:

1. Practical validation of the system's scientific and technical innovations;

2. Experimental evaluation of the platform's pedagogical effectiveness.

The AI-driven functionalities that constitute the scientific novelty of the ARD–KRT platform were successfully integrated and tested at the code level. The following outcomes summarize the key technical results.

Accuracy of Traceable Knowledge Extraction. Using GPT-4o, the system demonstrated a high level of precision in linking extracted learning concepts to their exact locations within the source materials.

- Localization Accuracy: The _call_openai_for_content_analysis function performed successfully across N = 30 analyzed resources, linking each concept to a specific page number (for PDF files) or timestamp ([MM:SS] for videos), and storing the data in the Resource.processed_content_data field.

- Technical Outcome: Among 215 extracted concepts, 93.4% contained correctly matched source_location attributes.

The generate_ai_test function constrained the GPT-4o model to produce test questions strictly based on the selected learning resources.

- Source Consistency: All M = 100 generated questions were accurately mapped to their corresponding content locations via the source_location field in the TestQuestion model.

- Relevance Rate: The average content–source alignment rate ($M_{av}g$ = 91.2%) indicated a strong coherence between generated items and their references.

- Scientific Significance: These findings demonstrate the feasibility of enhancing the transparency and traceability of generative AI outputs—shifting them from a "black box" paradigm to verifiable, source-linked assessment generation.

The two-step adaptive remediation mechanism proved particularly effective for students who initially provided incorrect responses.

- Stage 1 Effectiveness (Shallow Remediation): In the experimental group, 78.3% of students who failed the first attempt successfully corrected their answers after being redirected to the exact source_location of the relevant content.

- Cognitive Load Optimization: By directly pointing learners to the precise location of their knowledge gap, the ARD–KRT system reduced average re-learning time by 2.5× compared to the control group.

Throughout the experiment, a total of T = 580 adaptive recommendations were generated:

- Stage 1 (Source Redirection): 68.4% of all recommendations, where StudentTestAttempt = 0 and students were guided to the content source.

- Stage 2 (Deep Explanation): 31.6%, where StudentTestAttempt = 1 and the AI generated a comprehensive, personalized explanation.

Overall, the ARD–KRT system predominantly applied low-cognitive-load remediation strategies (68.4%) and activated deep, high-cognitive-load remediation (31.6%) only when the initial intervention was ineffective. These findings confirm the high efficiency of the adaptive approach in optimizing cognitive load and closing knowledge gaps.

DISCUSSION

The findings of this study confirm the effectiveness of the Adaptive Digital Didactic–Content Remediation System (ADD–CRS) in closing students' knowledge gaps and improving learning performance compared to conventional Learning Management Systems (LMS). Specifically, the platform's integration of AI-driven traceability and two-stage remediation mechanisms yielded measurable improvements, with 93.4% accuracy in source location mapping and a 78.3% success rate in gap closure during initial remediation attempts. These outcomes addressed two core scientific gaps identified in the introduction: the lack of content traceability and the inefficiency of adaptive remediation mechanisms in existing LMS environments [11].

Most adaptive learning systems relying on Artificial Intelligence (AI) still function as "black boxes," generating content without transparent linkage to original learning materials, which undermines academic credibility and instructional reliability[12]. For instance, while tools like GPT-4o excel in content generation, they often fail to maintain verifiable connections to source materials, leading to potential inaccuracies or unverifiable outputs in educational contexts[13]. This opacity not only erodes trust in AI-assisted assessments but also complicates pedagogical evaluation, as educators cannot easily trace generated items back to their origins[14].

In contrast, the ADD–CRS platform integrates a Traceable Knowledge Extraction mechanism implemented via the _call_openai_for_content_analysis function, which ensures transparent mapping between generated content and its verified source. By embedding metadata such as page numbers, slide references, or MM:SS timestamps directly into the extraction process, the system transforms opaque AI outputs into auditable artifacts. Empirical validation demonstrated 93.4% accuracy in identifying the precise source location of key concepts (e.g., page number, slide reference, or MM:SS timestamp in video materials), surpassing benchmarks from similar knowledge tracing models. This mechanism introduced a new dimension of scientific transparency into generative AI-driven content production, allowing educators to instantly verify the validity of AI-generated assessment items through the Generative Assessment feature (Advancing Generative Intelligent Tutoring Systems with GPT-4, 2024). As noted by Kasneci et al., such traceability not only enhances ethical AI use in education but also facilitates compliance with emerging standards for AI transparency in higher education[15].

Traditional remediation strategies typically provide either generic recommendations or cognitively overwhelming explanations to students who fail initial tests, often exacerbating rather than alleviating learning barriers. These approaches overlook the nuanced interplay between learner readiness and instructional design, resulting in suboptimal retention and increased frustration.

The ADD–CRS system introduced a two-stage adaptive re-learning methodology aligned with Cognitive Load Theory (CLT), which posits that instructional design should minimize extraneous load while maximizing germane load for schema construction. In the first stage, low-load interventions (e.g., direct source navigation) prioritize efficiency and self-directed discovery, drawing on principles of minimal guidance for novice learners. The second stage escalates to high-load, personalized deep explanations only when necessary, ensuring targeted support without overwhelming the learner.

During experimentation, in 68.4% of cases, learners in the experimental group first received low-load recommendations — direct navigation to specific source segments relevant to their errors. As a result, they successfully closed knowledge gaps 2.5 times faster than the control group, achieving a 78.3% success rate in remediation efficiency. This differential approach aligns with empirical evidence from adaptive tutoring systems, where tiered interventions have been shown to improve post-test performance by 20–40% compared to uniform strategies. These outcomes offer an evidence-based solution to the well-documented problem of ineffective re-teaching in digital learning environments, where one-size-fits-all remediation often leads to disengagement.

The results provide theoretical validation for applying the principles of traceability and source-based transparency in AI-driven education[14]. The ADD–CRS model demonstrates that generative AI systems can be effectively integrated into LMS frameworks as methodologically grounded instructional tools rather than opaque automation engines. By enforcing prompt constraints and metadata embedding, the platform mitigates common pitfalls of generative models, such as hallucination or drift from source fidelity, which have been reported in up to 30% of AI-generated educational content.

Furthermore, the Generative Assessment function substantially reduced educators' content preparation time by enabling automatic generation of source-linked test items, with an average alignment rate of 91.2%. This efficiency gain is particularly relevant in resource-constrained settings like Uzbekistan's higher education, where faculty workloads often limit innovative assessment design).

Despite these strengths, the study has limitations. The experiment was conducted with a sample of 50 undergraduate students in a single institution, potentially limiting generalizability; future work should include diverse cohorts[11]. Additionally, while GPT-4o provided robust performance, dependency on proprietary APIs raises scalability concerns in low-connectivity regions[15].

Future studies will focus on further enhancement of the ADD–CRS system through the integration of advanced AI-driven functionalities — including automated grading, synchronization of results with digital gradebooks, and automation of formative, midterm, and summative assessments. These advancements aim to fully digitize the evaluation process, reduce teacher workload, and ensure greater objectivity and consistency in assessment outcomes.

Ultimately, the ADD–CRS platform is envisioned to evolve beyond an adaptive remediation tool into a comprehensive, AI-empowered digital assessment ecosystem capable of supporting large-scale personalized learning and analytics-driven pedagogy[16]. By bridging the gap between AI potential and pedagogical practice, this system holds promise for transforming education in resource-limited contexts like Uzbekistan, fostering equitable access to high-quality, adaptive instruction.

CONCLUSION

This study successfully achieved its primary goal — the development and implementation of an AI-driven adaptive learning platform designed to enhance the effectiveness of digital education.

The proposed Adaptive Digital Didactic–Content Remediation System (ADD-CRS) provided a scientifically grounded solution to two critical methodological gaps identified in existing Learning Management Systems (LMS): content transparency and adaptive remediation efficiency.

The key scientific contribution of this research lies in the design and practical implementation of a two-stage adaptive re-learning methodology integrated within an AI-based system.

The ADD-CRS platform introduced two innovative mechanisms:

1. Traceable Knowledge Extraction — enabling precise identification of the original source location of educational content (e.g., Page N in PDFs or MM:SS timestamp in videos); and

2. Generative Assessment — allowing automatic creation of assessment items that are directly linked to their verified sources.

This approach introduced scientific transparency and source accountability into the generative AI process, ensuring that every question or learning element could be traced back to its original material with measurable accuracy.

Moreover, the two-stage adaptive feedback cycle effectively optimized cognitive load: students first received low-load, source-based guidance, followed by deeper conceptual explanation, which significantly accelerated the closure of knowledge gaps.

In summary, the research made a substantial theoretical and practical contribution to the methodology of AI integration in digital education.

The ADD-CRS model expanded the pedagogical capabilities of LMS platforms by incorporating adaptive, personalized, and cognitively optimized learning mechanisms.

Future research will focus on testing the ADD-CRS system across various subject domains and exploring its interoperability with multiple Large Language Models (LLMs) to further enhance its scalability and pedagogical adaptability.

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