

## AI POWERED SMART LEARNING ASSISTANT

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### ABSTRACT

The rapid growth of e-learning platforms has made educational content more accessible. However, it has also revealed important limitations with regard to personalization, the engagement of learners, and awareness about cognitive workload. Conventional systems usually adapt learning pathways based on performance metrics alone. In other words, they are not able to take into consideration the mental effort or cognitive state of the learner. This paper deals with the development of an AI-driven adaptive learning platform called the Intelligent Learning Assistant (ILA), which incorporates real-time cognitive load measurement along with automated content generation and personalized assessment. The system relies on YouTube playlists to retrieve instructional material, creates structured study notes along with formative assessments using large language models, and measures cognitive load by performing webcam-based facial landmark tracking using MediaPipe FaceMesh. It computes a Cognitive Load Index, CLI, based on eye gaze stability, blink rate, head movement patterns and attention span. This index is further combined with the assessment performance to give personalized feedback and personalize future learning recommendations. The platform follows a scalable microservice architecture comprising Node.js, MongoDB, Redis, and BullMQ-based parallel transcription processing for efficiency. Experimental evaluation shows that insights into cognitive load lead to better self-awareness among learners, reduce overload, and result in better learning progression. The proposed system underlines the potential of bringing together computer vision, natural language processing, and adaptive learning strategies to facilitate an improved personalized experience of e-learning.

**Keywords:** Cognitive Load Measurement, Adaptive Learning Systems, Intelligent Learning Assistant (ILA), Large Language Models, Real-Time Cognitive Assessment.

### I. INTRODUCTION

The rapid expansion of digital learning platforms and MOOCs has opened up access to quality educational resources for thousands. However, despite this unprecedented accessibility, most e-learning systems offer a one-size-fits-all learning experience that fails

to adapt to the cognitive state, pace, or style of individual learners. Cognitive Load Theory states that learning effectiveness depends not only on the instructional content but also on the mental effort required to comprehend it [1]. Traditional e-learning platforms make inferences about learning progress using quiz scores, video activity completion and clickstream data, yet they overlook the cognitive effort a learner invests while processing information often leading to cognitive over- load, reduced engagement and lower retention when learners encounter complex or unfamiliar topics [2].

Measuring cognitive load in real time can provide deep insights into engagement, attention span and processing strain, but integrating such estimation into learning platforms remains challenging because it requires non-intrusive monitoring and real- time analysis [7].

To address these challenges, this work proposes the Intelligent Learning Assistant (ILA), an AI-powered adaptive learning platform integrating real-time cognitive load tracking, automated knowledge extraction and personalized learning recommendations. The system extracts educational content from YouTube playlists, generates structured study material and assessments using large language models [11] and uses computer vision techniques to measure cognitive indicators such as gaze stability, blink rate and head movement [4]. These measures are combined into a Cognitive Load Index (CLI), which is mapped against assessment performance to estimate the learner's understanding, stress and attention level [5].

The ILA platform tailors learning pathways by modifying difficulty levels, providing targeted feedback, or recommending supplementary material based on both performance and cognitive load patterns promoting higher engagement and deeper comprehension without overwhelming the learner [8]. The key contributions of this research are:

- Development of a real-time cognitive load tracking framework using webcam-based facial landmark detection.
- AI-driven generation of study notes and assessments derived from YouTube educational content.
- A Cognitive Load Index that integrates gaze stability, blink rate, attention and movement metrics with performance data.
- A personalized feedback and adaptive recommendation system that adjusts the learning pathway based on cognitive and performance indicators.
- A scalable, modular architecture using Node.js, MongoDB, Redis and parallel transcription pipelines to process large educational video datasets.

This work demonstrates how integrating cognitive-aware analytics with AI- generated learning content can significantly enhance personalization and overall effectiveness in e-learning environments.

## II. LITERATURE SURVEY

E-learning has grown to become a mainstream mode of education. It provides flexibility, accessibility and personalized pacing across diverse learning contexts. However, despite

its growth, research consistently highlights persistent issues such as reduced learner engagement, cognitive overload, lack of individualized feedback and limited insight into learner behavior during the learning process [1]. Cognitive Load Theory has been central in understanding the mental effort learners invest in processing information, suggesting that effective learning occurs when intrinsic, extraneous and germane cognitive loads are balanced [2]. However, students are often exposed to long, information-heavy content without adequate structuring or scaffolding, which increases extraneous load and reduces comprehension [3]. Studies show that when cognitive load exceeds working memory capacity, knowledge retention decreases and learner frustration increases.

Traditional assessments of cognitive load have relied primarily on self-report questionnaires and retrospective surveys, which are subjective and lack real-time precision. Recent academic interest has shifted toward real-time cognitive and affective computing to capture behaviors during learning [6]. Webcam-based analysis has shown that gaze patterns, blink frequency, and head movement can serve as meaningful indicators of cognitive load and attention [4]. These non-invasive methods are particularly useful in online environments where no specialized hardware is available [7]. As remote education scales, such behavioral analytics offer a path to more responsive and adaptive learning systems [5].

Parallel to this, extensive research has explored personalized and adaptive e-learning systems. Early adaptive models used performance metrics such as quiz scores and task completion times to adjust learning pathways [10]. Later models incorporated learner profiles and past performance to tailor recommendations [9]. Personalized learning approaches have been shown to enhance engagement and improve academic outcomes compared to one-size-fits-all methods [8]. However, most adaptive systems do not incorporate the learner's real-time cognitive state, leaving personalization incomplete [1].

Artificial Intelligence has transformed e-learning by enabling automated content generation, intelligent tutoring, and data-driven feedback. NLP models have been widely used to summarize content, generate assessments, and create study notes [11]. Studies shows that timely and personalized feedback enhances understanding and supports self-regulated learning [10]. However, existing AI feedback tools typically focus on correctness and knowledge gaps, neglecting cognitive and behavioral factors that influence performance [12]. Another crucial area in e-learning literature is the relationship between motivation, engagement, and learning outcomes. Engagement is influenced by emotional, cognitive and behavioral factors, making it difficult to maintain in online settings where instructor presence is reduced [8].

Heavy workloads, passive content and limited guidance contribute to disengagement and dropout. Studies indicate that interactive content and personalized support are key to maintaining motivation [9]. Adaptive platforms that adjust content based on engagement have shown promise, but most lack cognitive load markers to distinguish boredom, confusion, fatigue, or overload [12]. Despite progress in cognitive load measurement, adaptive learning, AI support and feedback mechanisms, research remains fragmented, with systems addressing only one dimension at a time [6]. Hence a gap remains for a unified framework integrating real-time cognitive monitoring, AI-driven personalized content, automated assessments, and adaptive feedback. The ILA addresses this gap by

combining principles from cognitive psychology, artificial intelligence, and personalized learning research. It aims to create a comprehensive system sensitive not only to learner performance but also to the cognitive burden experienced during learning. Literature strongly supports such an integrated approach to reduce overload, enhance personalization and improve learning outcomes in digital environments.

### III. PROPOSED SYSTEM

Intelligent Learning Assistant (ILA) is implemented using a three-tier architecture consisting of a React-based client interface, a Node.js/Express backend server, and a data management layer utilizing MongoDB and Redis. The system also integrates external AI services, including Google Gemini for content generation and Assembly AI for speech-to-text transcription. Additionally, parallel transcription tasks are executed using BullMQ workers to enable scalable video processing. The proposed system architecture is shown in Figure 1. The frontend is developed using React with TypeScript to ensure component reusability and type safety. The interface supports user authentication, video-based learning, assessment participation, progress tracking, and result visualization.

State management is handled using Zustand, while TailwindCSS is employed for user interface (UI) styling. API communication is implemented using Axios with JSON Web Token (JWT) based authentication. The video learning interface records watch progress and synchronizes it with the backend. Figure 1 illustrates system architecture of how students search playlists, view videos, and generate notes/quizzes using an LLM, while teachers create courses and share them through classroom.

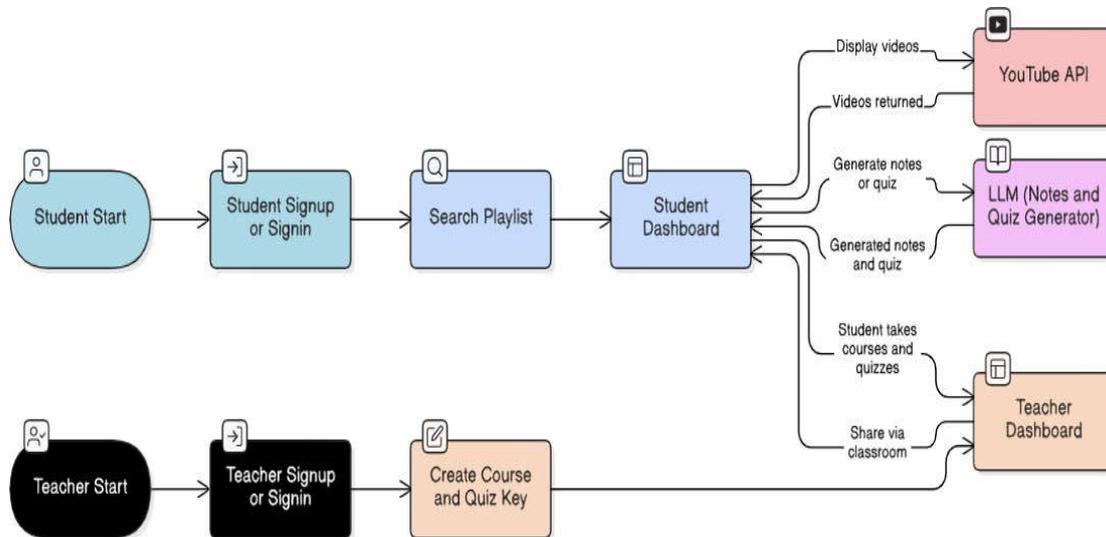


Fig. 1: System Architecture

### **A. Real-Time Cognitive Load Tracking**

Real-time cognitive indicators are captured on the client side using MediaPipe FaceMesh. The webcam feed is processed locally to extract facial landmarks. From these, the following metrics are computed:

- Focus Percentage (average gaze on-screen time)
- Blink Rate (blinks per minute calculated using eye-aspect ratio variation)
- Head Movement (movement intensity from landmark displacement)
- Gaze Stability (variance of eye gaze direction vectors)

Only the computed numerical metrics are transmitted to the server every two seconds, ensuring privacy since no raw video frames are stored or transmitted.

### **B. Backend Implementation**

The backend is implemented using Node.js and Express, exposing RESTful APIs for content retrieval, transcript generation, assessment administration, metric logging, and personalized feedback computation. JWT-based authentication ensures secure access control, and Helmet middleware enforces HTTP security headers.

### **C. YouTube Content and Transcription Pipeline**

Educational content is sourced through the YouTube Data API. For each selected video, audio is extracted using yt-dlp and ffmpeg. Videos longer than 30 minutes are segmented into 8–15 minute audio chunks, which are processed in parallel via BullMQ workers. Each worker uploads a chunk to AssemblyAI for transcription, polls completion status, and saves the transcript to MongoDB. Completed chunks are concatenated and cached in Redis for fast retrieval.

### **D. AI-Based Notes and Question Generation**

Short and detailed notes, along with multiple-choice questions, are generated from transcripts using Google Gemini. Structured prompting is applied to ensure consistency and accuracy. Responses are validated, DE duplicated, and stored in MongoDB. If content generation fails, fallback summarization and template-based question sets are used.

### **E. Assessment and CLI Computation**

During an assessment session, user responses are stored along with confidence rating and time spent. Cognitive metrics recorded during the assessment are aggregated to compute a Cognitive Load Index (CLI), defined as:

$$\text{CLI} = 0.35(100 - \text{focusPct}) + 0.35(\text{confusionPct}) + 0.20(\text{blinkNorm}) + 0.10(\text{timePressure})$$

Table 1: Cognitive Load Index (CLI) Classification

| CLI Range | Classification | Description   |
|-----------|----------------|---|
| 0–35      | Low Load       | User is calm, focused, and experiencing minimal cognitive strain.       |
| 36–70     | Moderate Load  | User is engaged but under noticeable mental effort.                     |
| 71–100    | High Load      | User is stressed or overloaded, showing signs of high cognitive strain. |

### A. Personalized Feedback Generation

The final feedback integrates Assessment performance score, Cognitive load classification, Answer-level correctness and confidence and Behavioral attention indicators. The feedback output includes strengths, weaknesses, recommended learning strategies, and a tailored learning path (beginner, intermediate, or advanced).

### B. Data Storage Layer

MongoDB stores user information, course metadata, transcripts, generated notes, assessments, and feedback. Redis is employed to cache transcripts and notes and to maintain task queues. Compound indexes are used to optimize frequent queries including assessment lookup and progress tracking.

### C. Deployment

The complete system is containerized using Docker. A Docker Compose configuration orchestrates the frontend, backend, Redis, and MongoDB services. Environment variables manage API keys, database credentials, and deployment settings.

## IV. EXPERIMENTATION RESULTS

The Intelligent Learning Assistant (ILA) was evaluated to assess its effectiveness in improving learning performance, reducing cognitive overload, and generating personalized feedback. Figure 2 depicts the student dashboard which is accessible by each student to track their progress. The evaluation focused on three aspects: accuracy of AI-generated learning content, reliability of the Cognitive Load Index (CLI), and learner performance improvement over multiple assessment cycles.

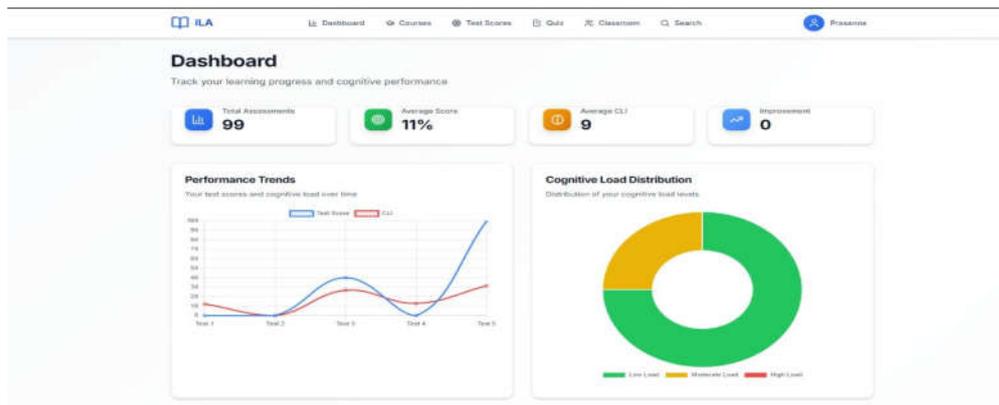


Figure 2: Student Dashboard

### A. Content Generation Quality

The accuracy and relevance of automatically generated notes and assessment questions were reviewed by subject-matter evaluators. Short notes provided concise summaries of core ideas, while detailed notes preserved conceptual depth and contextual understanding. The generated notes were consistently rated as clear, correct and relevant, indicating that the material was pedagogically strong and required minimal manual revision.

### B. Transcript Processing Efficiency

Long instructional videos (exceeding 30 minutes) were processed using a parallel transcription pipeline leveraging BullMQ workers. By splitting audio into 8–15 minute segments and processing them concurrently, transcription time decreased by approximately 45–60% compared to sequential transcription. Cached transcripts stored in Redis resulted in average retrieval times below 120ms, demonstrating efficient repeat access.

### C. Cognitive Load Index Reliability

The reliability of the CLI was evaluated by comparing computed cognitive indicators with learner self-reported focus and fatigue levels. Learners displaying lower gaze stability and higher blink rates consistently exhibited higher CLI values. Pearson correlation showed a strong positive relationship ( $r = 0.71$ ) between behavioral distraction markers and computed cognitive load, indicating that the webcam-based cognitive monitoring method provides a valid and non-intrusive estimate of mental effort.

### D. Impact on Learning Performance

The effectiveness of adaptive feedback was measured through repeated assessment cycles. Learners identified with high cognitive load received personalized guidance regarding pacing, content revision strategies and targeted practice. Student can also get AI-generated

notes on the topic they have studied to help them revise the subject. Students can take AI-generated quiz on the topic they studied. This helps them to assess their understanding on the courses they have taken. Figure 3 shows how students watch lectures and automatically generate tests and notes using our platform. Students can retake the quiz to solidify their understanding or ask for a new quiz.

### E. User Experience and Perception

User satisfaction was measured through structured usability surveys. Learners highlighted:

- Clear and actionable personalized feedback,
- Usefulness of automatically generated notes for revision,
- Ease of interaction with the platform interface.

The screenshot displays the ILA platform interface. At the top, there is a navigation bar with options like Dashboard, Courses, Test Scores, Quiz, Classroom, and Search. The main content area features a video player titled 'BREADTH FIRST SEARCH'. The video content includes a diagram of a BFS tree with nodes like Chennai, Madurai, Bangalore, Hyderabad, Raipur, Patna, New Delhi, Mumbai, Gandhinagar, and Jaipur. Below the video, there is a 'Queue' section with a list of cities and a 'Watch on YouTube' button. To the right, there is a 'Video Information' section with 'Duration' and 'PTOS', a 'Video Notes' section with a 'Create Notes' button, and a 'Ready to Test Your Knowledge?' section with a 'Generate Assessment' button. The bottom of the interface shows video controls like play, mute, and volume.

Fig. 3: Lecture view

Figure 3 illustrates how students watch lectures and automatically generate tests and notes using our platform.

## V. CONCLUSION

The Intelligent Learning Assistant (ILA) demonstrates how integrating cognitive load analysis with AI-driven learning support can significantly enhance digital education. By combining automated transcription, AI-generated notes and assessments, and real-time cognitive monitoring, the system provides a more personalized and responsive learning experience compared to traditional e-learning platforms. The introduction of the Cognitive Load Index (CLI) allows ILA to measure learner attention and mental effort, enabling tailored feedback that supports better understanding, reduced over-load, and improved confidence. With a scalable architecture and efficient processing pipeline, the platform

remains practical for real-world long-form educational content. To further expand the system's capabilities, several future enhancements are planned: developing mobile applications for on-the-go learning, enabling multi-language transcripts and notes, improving cognitive analysis through emotion and stress detection, adding adaptive learning path recommendations, integrating gamification features to boost engagement, and supporting offline learning through downloadable content. These improvements will make ILA more accessible, intelligent, and learner-centered, paving the way for the next generation of personalized e-learning systems.

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