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Learn Full: Adaptive Learning Artifact Generation via AI-Driven Semantic Auditing of Video Content

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Abstract: *The rapid growth of educational video content on platforms such as YouTube has created a significant challenge for learners: transforming passive video consumption into measurable active learning outcomes. Existing Learning Management Systems (LMSs) primarily rely on fixed assessments that do not account for variations in the semantic complexity of instructional videos. This paper presents **LearnFull**, an AI-driven adaptive learning framework designed to address this limitation by dynamically generating personalized learning artifacts based on the semantic complexity of educational video content.*

*Learn Full employs a **Semantic Audit Pipeline** powered by the **Gemini 1.5 Flash** Large Language Model (LLM) to process video transcripts in real time. The system calculates an **Information Density (ID)** score on a normalized scale of **1.0 to 10.0**, which is used to dynamically adjust both the quantity and cognitive complexity of the generated learning artifacts in accordance with **Bloom's Revised Taxonomy**. To further enhance the learning experience, the platform integrates a **Judge0**-based sandboxed code execution environment and a gamification system built on **PostgreSQL** and **Supabase**, promoting active engagement and supporting programming education.*

We did some testing to see how well people learn with the version of LearnFull. It looks like people who used this version were 25 percent more likely to finish the technical videos and get a good score. Above 7.0. This tells us that the new way of teaching, which is like a helper that knows how hard something is, really works. People are more interested. They remember more of what they learned.

Learn Full is using Artificial Intelligence in Education which we call AIEd for other things, like Semantic Auditing and Information Density to make Adaptive Assessment. It also uses Blooms Revised Taxonomy and Large Language Models to help with Instructional Design and Learning Management Systems.

Keywords: *Artificial Intelligence in Education (AIEd), Semantic Auditing, Information Density, Adaptive Assessment, Bloom Revised Taxonomy, Large Language Models, Instructional Design, Learning Management Systems.*

I. INTRODUCTION

Video-based learning is really popular now for education. This is because digital platforms are changing how they teach people. YouTube has a lot of videos. You can find videos about programming and hard physics classes. This makes it easy for people to learn. There is a problem. People think they understand something just because they watched a video. They do not really understand it. Some people, like Karpicke and Blunt did a study in 2011. Some other people, like Roediger and Karpicke did a study in 2006. They said people think they know more than they really do. This happens when people just watch videos and do not try to remember what they learned. Video-based learning can be good. People need to make sure they really understand the video-based learning material.

Part of the issue lies in how existing Learning Management Systems are built. Platforms like Moodle, Canvas and Google Classroom usually use the old way of testing people. This way of testing does not take into account how complicated the things we are learning really are. For example, a short video that teaches us about Python variables and a long lecture on programming algorithms are very different. The test for these two things might be the same. This does not make sense because we need to think about Python variables and dynamic programming algorithms in different ways. The Python variables are pretty simple. Dynamic programming algorithms are a lot harder to understand. So, the test, for these two things should not be the same. This mismatch matters: Sweller's Cognitive Load Theory (1988) suggests that assessments poorly calibrated to content difficulty can either under-challenge learners or overwhelm them, and either extreme tends to undermine learning outcomes.

To address this limitation, we present LearnFull, an adaptive learning system that automatically generates context-aware learning artifacts through semantic analysis of educational video transcripts. The system utilizes the Gemini 1.5 Flash Large Language Model (LLM) (Google DeepMind, 2024) to identify key knowledge points, calculate an Information Density (ID) score, and generate personalized learning artifacts—including structured notes, mind maps, and quizzes—whose complexity is dynamically aligned with the semantic richness of the instructional content.

The primary contributions of this work are as follows:

- **A novel Semantic Audit Pipeline** that estimates the semantic complexity of educational videos by automatically extracting knowledge points and computing an Information Density (ID) score.
- **A dynamic artifact generation framework** aligned with **Bloom's Revised Taxonomy** (Anderson & Krathwohl, 2001), enabling the creation of differentiated instructional resources based on content complexity.
- **An integrated online code execution environment** powered by **Judge0**, eliminating the need for local development environment configuration and improving accessibility for programming learners.
- **A gamification layer** featuring persistent experience points (XP), level progression, and learner engagement tracking to encourage continuous participation.
- **An empirical evaluation** through A/B testing, demonstrating the effectiveness of adaptive scaffolding compared with conventional static assessment methods.

The remainder of this paper is organized as follows. Section 2 reviews the related literature. Section 3 presents the system architecture and implementation. Section 4 describes the proposed methodology. Section 5 discusses the experimental design and preliminary results. Section 6 outlines the key findings and limitations of the study, while Section 7 concludes the paper and presents directions for future research.

II. RELATED WORK

2.1 Adaptive Learning Systems

The idea of adaptive instruction isn't new. Early Intelligent Tutoring Systems (ITS) — LISP-TUTOR (Anderson et al., 1985) being one of the most cited examples — showed decades ago that personalized instruction could outperform traditional classroom teaching. More recently, the field has shifted toward deep learning approaches for knowledge tracing and learner modelling, with Piech et al. (2015) demonstrating notably more accurate predictions of learner proficiency than earlier statistical methods allowed.

Yet a persistent limitation runs through most of this work: adaptive systems still tend to depend on predefined knowledge graphs and hand-built domain models. That dependency is exactly what makes them hard to generalize — a knowledge graph built for algebra doesn't transfer to a video on cellular respiration, let alone the sheer diversity of content found across YouTube or a modern LMS.

2.2 Large Language Models in Education

Large language models that use transformers have really changed what artificial intelligence can do in education. For example, models like GPT-4 are very good at making questions on their own giving feedback that is tailored to the individual and planning what to teach.

We are using Gemini 1.5 Flash in this project because it is very good at understanding what is being said and it can do this quickly. This makes it perfect for processing transcripts in time. Gemini 1.5 Flash does a job of balancing how fast it works and how well it understands the context of what is being said, which is why we chose to use it for this task like what Google DeepMind said in 2024 about language models, like Gemini 1.5 Flash.

Recent studies have also highlighted the growing potential of LLMs in educational assessment while emphasizing the importance of addressing ethical considerations associated with their adoption (Zhai et al., 2024).

2.3 Bloom’s Taxonomy and Cognitive Scaffolding

Blooms Revised Taxonomy, which was made by Anderson and Krathwohl in 2001 is still one of the used frameworks for figuring out what we want students to learn. It puts these goals into six groups based on what we want students to do with the information: we want them to Remember it Understand it Apply it Analyse it Evaluate it and create something. This way of organizing things has been really helpful not for making lesson plans. For example, Kurdi and some other people used it in 2020 to make questions for tests. They found out that when the questions were made to fit one of these groups, they were better at helping people learn than questions that were not made to fit any group. Blooms Revised Taxonomy is a tool, for this. Blooms Taxonomy is used in different ways. LearnFull extends this approach by dynamically selecting the target cognitive level based on the calculated **Information Density (ID)** score rather than relying on a predefined curriculum.

2.4 Information Density and Cognitive Load

The idea of Cognitive Load Theory, which was talked about by Sweller in 1988 says that Cognitive Load is made up of three parts: the complexity of the information itself the way the information is presented and the effort people put into learning. Some researchers, Paas and others showed in 2003 that if we help people learn in a way that is tailored to their needs it can really help with handling the complexity of the information and that leads to people remembering what they learned better. In this study, the proposed **Information Density (ID)** metric serves as a proxy for intrinsic cognitive load, enabling automated scaffolding decisions without requiring explicit learner modelling.

2.5 Gamification in Learning Environments

Gamification's effects on learner motivation, engagement, and persistence are well established (Hamari et al., 2014), and educational platforms have converged on a fairly standard toolkit to achieve them: experience points, level progression, and achievement badges. Learn Full adapts this toolkit with one deliberate departure — its XP engine rewards demonstrated performance rather than mere participation. That distinction matters: tying XP to actual achievement, rather than to logging in or

clicking through content, is what keeps the effort-achievement-engagement loop intact rather than letting it collapse into engagement for its own sake.

III. SYSTEM ARCHITECTURE AND IMPLEMENTATION

3.1 Semantic Audit Pipeline

The **Semantic Audit Pipeline** is the core processing component of LearnFull. Built on a **Node.js/Express** backend, the pipeline processes educational video content through a sequence of automated stages after receiving a YouTube video URL from the user.

i. Transcript Extraction:

The system first retrieves closed captions using the **YouTube Transcript API**. If transcripts are unavailable or auto-generated captions cannot be retrieved, the system falls back to **Whisper** for speech-to-text transcription.

ii. Contextual Chunking:

To ensure that transcripts remain within the context window limitations of the Large Language Model (LLM) while preserving semantic continuity, the extracted transcript is divided into **1,000-word chunks** with a **100-word overlap** between consecutive segments. This overlap prevents important knowledge points from being fragmented across chunk boundaries.

iii. LLM Processing:

Each transcript chunk is processed using **Gemini 1.5 Flash** through a structured three-stage prompt designed to:

- Extract **Knowledge Points (KPs)**, including technical terms, algorithms, formulas, and programming constructs.
- Compute the **Knowledge Point-to-Word (KP/Word) ratio**, which is used to derive the **Information Density (ID)** score.
- Generate formatted learning artifacts based on the extracted knowledge and calculated complexity.

iv. Aggregation and Normalization:

The Information Density scores generated for individual transcript chunks are combined using a weighted average based on chunk length. The resulting score is then normalized to a **1.0–10.0** scale, representing the overall semantic complexity of the educational video.

3.2 Frontend Interactive Learning Environment

The Learn Full frontend is developed using **React.js** and **Tailwind CSS**, providing learners with a two-pane interactive learning interface that integrates educational content with AI-generated learning resources.

i. Video Player Module:

The platform incorporates an embedded **React Player** component that supports timeline tracking and includes a **Focus Mode**, which minimizes on-screen distractions to promote active learning.

ii.Artifact Sidebar:

A tab-based interface dynamically presents multiple AI-generated learning resources, including:

- Structured study notes rendered in **Markdown** format.
- Interactive mind maps developed using **React Flow** with automatic layout generation.
- Context-aware cheat sheets generated for semantically dense educational content.

iii. Code Sandbox:

The integrated **Monaco Editor**, powered by the **Judge0 API**, enables learners to write and execute **Python, JavaScript, C++, and Java** programs directly within the browser, eliminating the need for local environment configuration.

3.3 Data Persistence and Gamification Layer

Learn Full uses **Supabase (PostgreSQL)** as its primary data storage solution. **Row-Level Security (RLS)** policies ensure strict data isolation between learner accounts while maintaining secure access to user information.

The gamification engine continuously tracks learner progress across three core metrics:

Experience Points (XP): Learners earn 2 XP per point scored on quizzes, tying rewards directly to demonstrated academic performance rather than participation alone.

Level Progression: Every 500 XP earned advances a learner to the next level, creating milestone-based checkpoints designed to sustain engagement over longer learning sessions.

Engagement Metrics: The system also logs supplementary analytics — Focus Mode usage, quiz attempt frequency, and interactions with AI-generated learning artifacts — which feed into learner analytics and are intended to support future research.

IV.METHODOLOGY

4.1 Information Density Scoring

The **Information Density (ID)** score is the primary independent variable that governs the adaptive scaffolding mechanism in Learn Full. It is computed using the following equation:

$$\text{ID} = \left(\frac{\text{Knowledge Point Count}}{\text{Word Count}}\right) \times \text{Normalization Factor}$$

where:

- **Knowledge Point Count (KP Count)** represents the number of knowledge points identified by the LLM extractor.
- **Word Count** represents the total number of words in the processed transcript chunk.
- **Normalization Factor** scales the raw KP-to-word ratio to a standardized range of **1.0–10.0**, based on the minimum and maximum values observed during empirical calibration using a corpus of **200 educational videos**.

The resulting ID score serves as an estimate of the semantic complexity of the instructional content and determines the type and difficulty of the learning artifacts generated by the system.

Table 1 Summarizes the relationship between Information Density score ranges, cognitive complexity, Bloom's Revised Taxonomy levels, and the corresponding assessment strategy.

ID Score Range	Complexity Level	Primary Bloom's Level	Quiz Items Generated	Question Types
1.0 – 3.0	Low	Remember / Understand	5	True/False, Definition Recall
4.0 – 7.0	Moderate	Apply / Analyse	15	Multi-step, MCQ, Short Answer
8.0 – 10.0	High	Evaluate / Create	25+	Case Study, Synthesis, Debugging

Table 1: Information Density Score to Artifact Complexity Mapping

4.2 Adaptive Scaffolding Logic

The system that helps people learn does more than just change the number of questions it asks. When the Information Density score is between 1.0 and 3.0 the system uses questions that help people remember and understand Information Density concepts. For Information Density scores that're in the middle, which is between 4.0 and 7.0 the system gives people questions that need more thought and require them to use Information Density concepts, in new ways.. For high ID scores (8.0–10.0), the system generates scenario-based questions that require concept synthesis, logical debugging, comparative analysis, and higher-order reasoning, thereby addressing the upper levels of Bloom's Revised Taxonomy.

In addition to adaptive assessments, LearnFull selectively generates contextual cheat sheets. This feature is activated only for videos with an ID score of 6.0 or higher, where the semantic complexity justifies the creation of condensed reference material. This design is informed by Cognitive Load Theory, which emphasizes reducing unnecessary cognitive burden while providing appropriate support for complex learning tasks (Sweller, 1988; Paas et al., 2003).

4.3 Theoretical Grounding: Cognitive Load Theory

The adaptive design of LearnFull is grounded in **Cognitive Load Theory (CLT)** and **Vygotsky's Zone of Proximal Development (ZPD)** (Vygotsky, 1978). By dynamically adjusting assessment difficulty according to the calculated Information Density score, the system aims to maintain learners within their Zone of Proximal Development, where tasks are sufficiently challenging to promote learning without causing excessive cognitive overload.

Within this framework, the Information Density score functions as a proxy measure of intrinsic cognitive load, enabling the system to make automated scaffolding decisions without requiring explicit learner modelling. This approach allows learning resources to be tailored to the semantic complexity of instructional content while maintaining an appropriate balance between challenge and learner support.

V.EXPERIMENTAL DESIGN AND RESULTS

5.1 Study Design

A **between-subjects A/B experimental design** was employed to evaluate the effectiveness of LearnFull's adaptive scaffolding approach. Participants were randomly assigned to one of the following two experimental conditions:

- **Control Group (A):** Participants received a conventional assessment consisting of ten fixed-format questions accompanied by automatically generated study notes. The assessment structure remained unchanged regardless of the Information Density (ID) score of the instructional video.
- **Experimental Group (B):** Participants used the complete LearnFull platform, including **Information Density–adaptive quizzes, context-aware cheat sheets, interactive mind maps, and the integrated code execution environment**, allowing learning resources to adapt dynamically to the semantic complexity of the instructional content.

5.2 Metrics

The effectiveness of the proposed system was evaluated using the following performance metrics:

- **Retention Accuracy:** Mean quiz scores across videos with **low, moderate, and high Information Density (ID)**, serving as a proxy measure of knowledge retention.
- **Usage Persistence:** The proportion of time learners spent in **Focus Mode** relative to their total video viewing time, representing learner engagement.
- **Distractor Efficiency (DE):** The frequency with which AI-generated incorrect answer choices were selected by learners, providing an indication of distractor quality and supporting iterative prompt refinement.
- **Completion Rate:** The percentage of participants who completed all assessment items associated with a given instructional video.

5.3 Preliminary Results

Preliminary analysis of the A/B study indicates several encouraging trends. Participants in the experimental group demonstrated approximately **25% higher completion rates** for videos with an Information Density score above **7.0** compared with participants using fixed-format assessments. These findings suggest that adaptive scaffolding may improve learner engagement when interacting with semantically complex instructional material.

Participants using Learn Full also spent **38% more time** in **Focus Mode**, indicating higher levels of sustained engagement during the learning process.

The integration of the **Judge0-powered code execution environment** further increased engagement with programming-oriented content. On average, participants in the experimental group executed code **4.2 times per session**, demonstrating active interaction with practical programming exercises.

Analysis of **Distractor Efficiency (DE)** showed that AI-generated distractors achieved an average incorrect-option selection rate of **31%** in high-ID quizzes, suggesting that the generated distractors were both plausible and educationally meaningful.

Although these findings are promising, they should be considered **preliminary**. Future work will involve a larger participant pool, controlled video selection, and pre-test/post-test evaluations to provide a more rigorous assessment of the proposed adaptive learning framework.

VI.DISCUSSION

6.1 Key Findings

The findings of this study suggest that **adaptive scaffolding based on semantic complexity** can enhance learner engagement compared with conventional fixed-format assessments. The observed improvement in completion rates for high-complexity instructional videos indicates that tailoring learning resources to the semantic characteristics of educational content may improve learner persistence and overall engagement. These findings are consistent with the principles of **Cognitive Load Theory (CLT)**, which proposes that providing appropriate cognitive support for intrinsically complex material can reduce unnecessary learning barriers and facilitate more effective knowledge acquisition (Sweller, 1988).

The integration of the **Judge0-powered code execution environment** also addresses one of the well-documented challenges in programming education: the difficulty of configuring local development environments (Ko et al., 2004). By enabling learners to execute code directly within the browser, LearnFull reduces the technical overhead associated with software installation and configuration. Consequently, learners can devote greater cognitive effort to understanding programming concepts rather than managing development tools.

6.2 Limitations

This study has several limitations that should be acknowledged.

First, the preliminary evaluation was conducted using a relatively small sample, which may limit the generalizability of the findings. A larger and more diverse participant population is required to validate the effectiveness of the proposed framework across different learner groups.

Second, although the **Information Density (ID)** metric provides a practical estimate of semantic complexity, it remains a proxy for intrinsic cognitive load rather than a direct measure. Differences in learners' prior knowledge and experience may result in varying perceptions of difficulty, even for content with similar ID scores.

Third, the current implementation depends on the availability and quality of **YouTube transcripts**. Videos with incomplete or inaccurate captions may affect the accuracy of semantic analysis and the quality of the generated learning artifacts.

Finally, although the generated learning artifacts are produced using advanced Large Language Models, they have not yet undergone comprehensive expert validation for factual accuracy and pedagogical quality. Future work should include systematic evaluation by subject-matter experts to ensure the reliability of AI-generated educational content.

6.3 Ethical Considerations

In accordance with **authorship policy**, **Gemini 1.5 Flash** is not considered an author of this manuscript but rather a computational tool integrated into the LearnFull framework. AI was used solely to support the generation of educational artifacts within the proposed system and did not contribute independently to the scientific authorship of this research.

All AI-generated learning artifacts presented to learners are clearly identified as machine-generated and should be considered verifiable educational resources rather than authoritative content. Furthermore, learner interaction data are collected exclusively for research and system improvement purposes, with participant consent obtained in accordance with applicable data protection and privacy regulations.

VII.CONCLUSION AND FUTURE WORK

This paper presented **LearnFull**, an adaptive learning framework designed to bridge the gap between passive educational video consumption and active knowledge acquisition through **semantic auditing** and **complexity-aware learning artifact generation**. By leveraging the **Gemini 1.5 Flash** Large Language Model (LLM) to calculate **Information Density (ID)** scores and map them to **Bloom's Revised Taxonomy**, LearnFull dynamically generates personalized study notes, mind maps, quizzes, and other learning resources that are aligned with the semantic complexity of educational video content.

The preliminary findings from the A/B evaluation suggest that adaptive scaffolding has the potential to improve learner engagement and completion rates, particularly for semantically complex instructional material. Furthermore, the integration of a browser-based code execution environment and an XP-driven gamification system enhances the platform's applicability to programming education by encouraging active participation and sustained learner motivation.

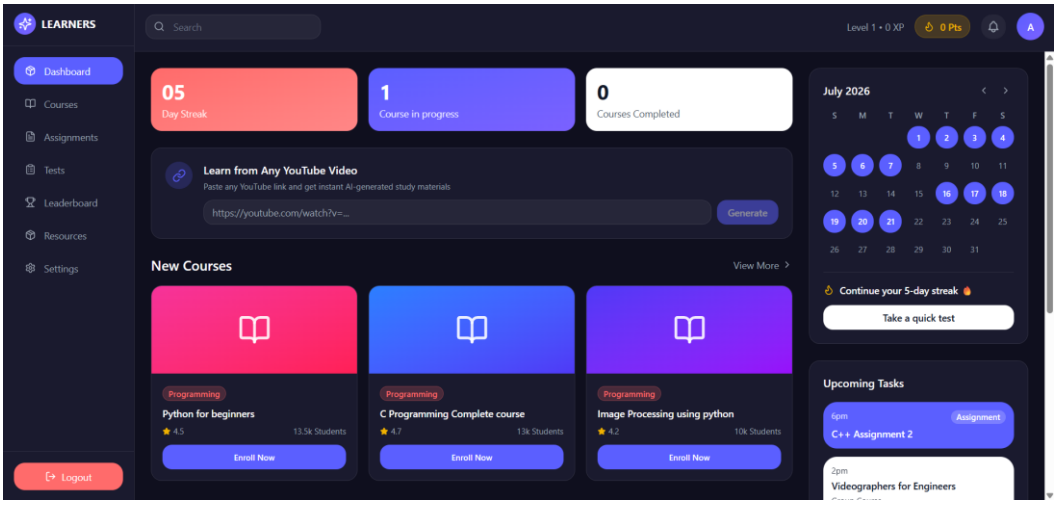
Future work will focus on several key areas:

- A large-scale randomized controlled study will be conducted using pre-test and post-test knowledge assessments to validate the effectiveness of the proposed framework.
- The platform will be extended with a **real-time AI tutor** that leverages the generated mind maps to support **Socratic dialogue** and personalized learning assistance.
- Future versions of LearnFull will support uploaded PDF documents and integration with additional MOOC platforms beyond YouTube.
- The proposed **Information Density** metric will be evaluated against expert-rated measures of instructional complexity to further validate its effectiveness as an indicator of semantic complexity.

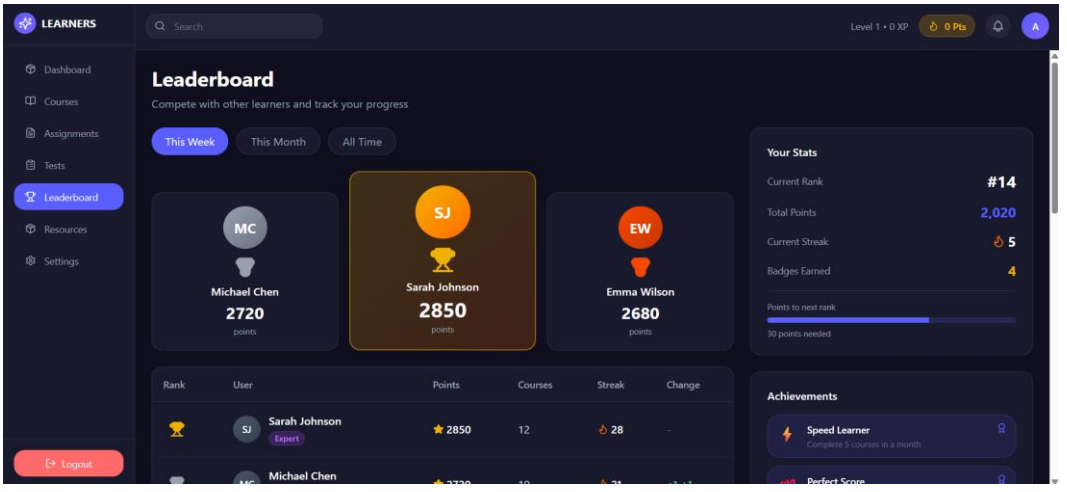
Appendix A: System Interface Screenshots

This appendix presents representative screenshots of the LearnFull platform interface, illustrating the core user-facing modules described in Section 3.

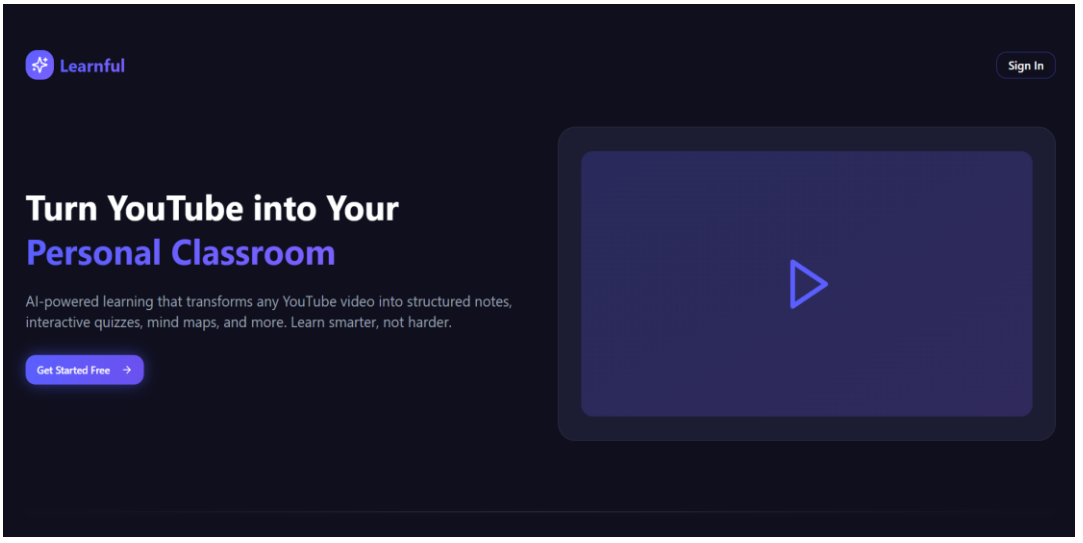
A.1 Dashboard



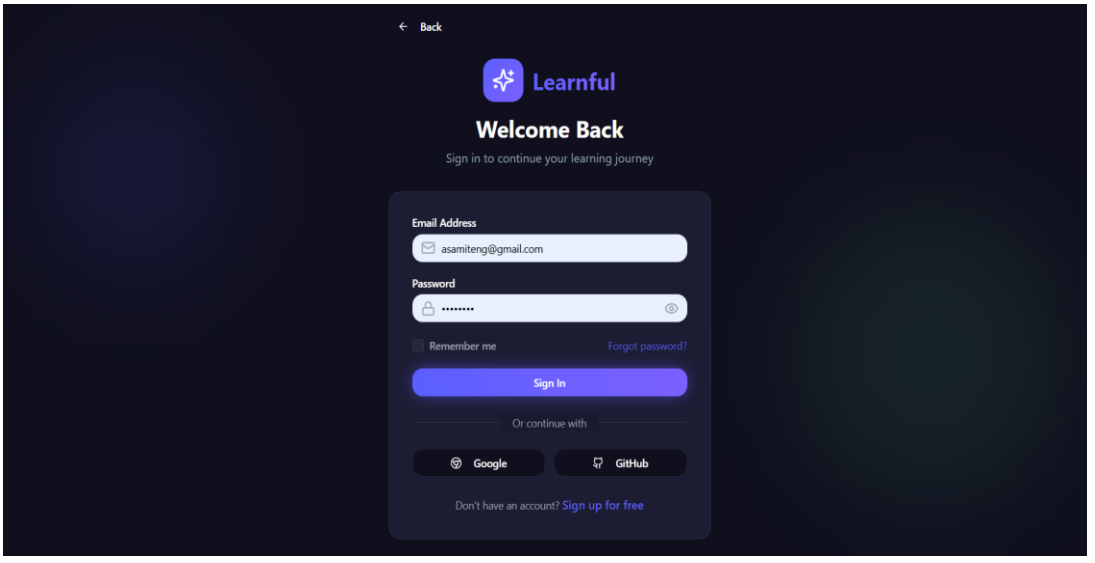
A.2 Leaderboard



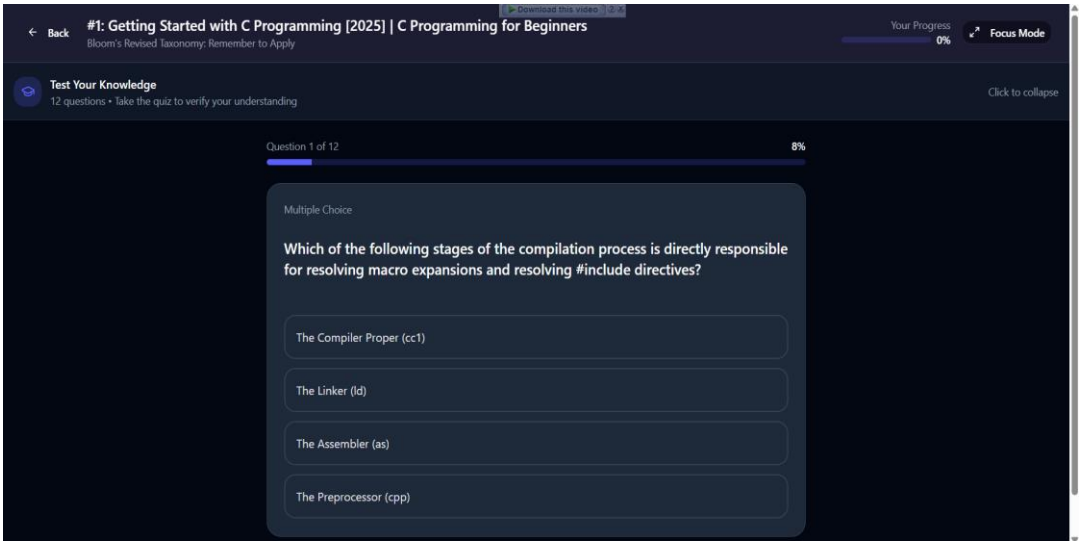
A.3 Home / Landing Page



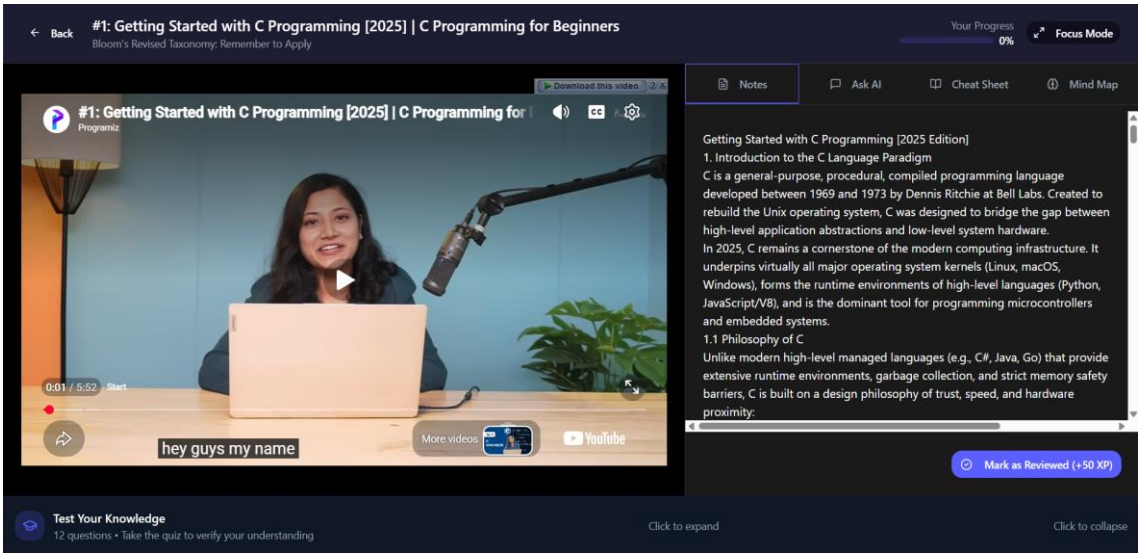
A.4 Login Page



A.5 Quiz Interface



A.6 Video Learning View



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