

# LLM Based models on personalized learning materials

A Project Report submitted in partial fulfillment of the requirements for the award of the degree  
of

## **BACHELOR OF TECHNOLOGY IN COMPUTER SCIENCE AND ENGINEERING**

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## **DECLARATION**

I hereby declare that the project titled “LLM based Model to personalized learning materials” is an original work carried out by us under the guidance of Dr. Katragada Sharada. This project has not been submitted to any university or institution for the award of any degree, diploma, or certification. We further declare that this project adheres to the principles of academic integrity and has not involved any form of plagiarism or unauthorized assistance.

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**CERTIFICATE**

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Date : 25/11/2025

Project Guide

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## ACKNOWLEDGEMENT

We express our profound and sincere gratitude to the **Department of Computer Science and Engineering, GITAM School of CSE, GITAM (Deemed to be University), Visakhapatnam**, for providing us with the opportunity, resources, and academic environment to successfully undertake and complete our capstone project titled **“LLM based Model to personalized learning materials.”** The department’s commitment to academic excellence and continuous support has been instrumental in enabling us to explore, research, and work on a project of such technical and societal significance in the domain of Generative AI safety.

We owe our deepest appreciation to our esteemed guide, **Dr. Katragadda Sharada**, for her exceptional mentorship throughout the duration of this project. Her insightful suggestions, constructive feedback, and unwavering encouragement consistently motivated us to refine our ideas and enhance the quality of our work. Her expertise in the field, coupled with her patient and dedicated guidance, played a vital role in shaping our understanding and directing our efforts effectively.

We further extend our heartfelt thanks to all the **faculty members, coordinators, and technical staff** of the department for their continuous assistance, timely support, and valuable academic inputs. Their dedication toward fostering a collaborative and research-driven environment greatly contributed to the smooth and successful progress of our project.

We would also like to acknowledge the invaluable support received from various academic and technical communities. Research publications, online documentation, open-source frameworks such as **Hugging Face** and **PyTorch**, and cloud-based computational tools like **Google Colab** significantly enriched our understanding of Large Language Models and Retrieval-Augmented Learning Systems. These resources provided a strong foundation for refining our methodologies, validating our approach, and enhancing the overall impact of our work.

Finally, we gratefully acknowledge the **teamwork, collaboration, and mutual support** within our project group. The coordinated effort, shared responsibility, and collective problem-solving approach were instrumental in the successful completion of this capstone project.

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## ABSTRACT

Traditional self-study tools and open-domain Large Language Models (LLMs) provide learners with rapid access to explanations and problem-solving assistance. However, their responses are typically derived from broad internet-scale datasets, resulting in terminology, reasoning styles, and solution methods that often differ from the instructor’s prescribed textbook or syllabus. This misalignment limits their reliability in formal educational settings and creates inconsistency in student learning outcomes. To bridge this gap, we propose an **LLM-Based Personalized Learning Material Generation System** that produces accurate, syllabus-aligned, and adaptive learning content grounded exclusively in instructor-provided materials.

The proposed system ingests textbooks and lecture slides, performs semantic chunking, and constructs a structured, vectorized knowledge base to enable precise information retrieval. Through a Retrieval-Augmented Generation (RAG) pipeline, the model generates explanations and study materials strictly anchored to source documents, eliminating hallucinations and ensuring academic fidelity. To further tailor the model's instructional behavior, Parameter-Efficient Fine-Tuning (PEFT) with LoRA adapters is employed to align the LLM’s reasoning style, vocabulary, and explanation patterns with course pedagogy.

An adaptive questioning framework evaluates student responses, adjusts difficulty dynamically, identifies misconceptions, and delivers targeted remediation pathways, enabling a personalized learning experience similar to expert human tutoring. Additionally, a comprehensive analytics module tracks mastery progression, learning trajectories, and conceptual weaknesses, providing instructors with transparent insights into student performance. This work presents an integrated, end-to-end solution combining semantic document understanding, grounded LLM reasoning, adaptive pedagogy, and real-time analytics—advancing the development of trustworthy, scalable, and academically aligned AI-assisted learning systems.

## INTRODUCTION

The rapid growth of Large Language Models (LLMs) has transformed the landscape of digital learning, offering students instant explanations, on-demand problem solving, and access to a vast knowledge base. However, despite their impressive capabilities, existing AI learning tools are fundamentally misaligned with the realities of formal education. Most models generate answers based on generalized internet-scale data, often introducing terminology, examples, or solution methods that differ from those presented in classroom instruction or prescribed textbooks. This disconnect creates confusion for learners and limits the practical adoption of AI-based assistance in academic environments that demand strict syllabus adherence and precision.

At the same time, students face an overwhelming challenge: processing lengthy textbooks, identifying essential concepts, and structuring their study plans according to course outcomes. Human tutors can provide personalized guidance, but such resources are not readily scalable. Current digital learning platforms also tend to be static, linear, and non-adaptive, failing to adjust teaching strategies based on individual learning pace, strengths, or misconceptions. Thus, there exists a critical need for an intelligent system that combines the flexibility of LLMs with the rigor of curriculum-aligned pedagogy.

This project addresses these challenges by proposing an **LLM-Based Personalized Learning Material Generation System**, designed to transform instructor-provided content—textbooks, lecture slides, and academic notes—into dynamic, adaptive, and personalized learning pathways. The system is built on a multi-layered architecture integrating modern AI techniques such as **Document Ingestion Pipelines**, **Semantic Chunking**, **Embedding-Based Knowledge Structuring**, **Retrieval-Augmented Generation (RAG)**, **LoRA-based Pedagogical Fine-Tuning**, and **Adaptive Questioning Algorithms**. Together, these components ensure that every explanation, summary, study plan, or practice question produced by the model is grounded exclusively in the instructor’s material, eliminating hallucinations and ensuring academic integrity.

The workflow begins with automated document ingestion, where raw textbook pages or PPT slides are converted into structured, machine-interpretable content. Using semantic chunking and dense embeddings, the system organizes this material into a hierarchical knowledge base optimized for retrieval. The Intelligent Reasoning Layer then uses Retrieval-Augmented

Generation to ensure that all responses are contextually precise and syllabus-aligned. The Learning Personalization Layer modifies the traditional LLM behavior by incorporating adaptive questioning and difficulty modulation, enabling the system to evaluate student understanding and dynamically adjust learning paths. Finally, the Monitoring and Analytics Layer tracks performance metrics and mastery progression, providing both students and instructors with actionable insights.

Through this integrated approach, the proposed system redefines how learning materials are generated and consumed, making personalized, high-fidelity academic support accessible at scale. By combining the power of LLMs with pedagogical structure, retrieval grounding, and adaptive intelligence, the system bridges the gap between artificial intelligence and formal education—ensuring that students not only learn faster, but learn exactly what they are meant to learn, in the way their instructors intend.

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## LITERATURE SURVEY

**3.1 Textbook Question Answering (Kim et al., EMNLP 2018):** The TQA dataset introduced multimodal comprehension tasks derived from science textbooks. It highlighted that structured conceptual knowledge requires deeper contextual linking compared to open-domain text sources. This finding showed that textbooks contain hierarchical, cumulative concepts that LLMs must process differently from general web data. These insights directly shaped our approach to semantic chunking, context preservation, and concept-level embeddings in the proposed system.

**3.2 Knowledge Graph-Enhanced RAG for Tutors (Dong et al., 2023):** Dong et al. demonstrated that augmenting retrieval results with knowledge graphs dramatically improves alignment and consistency in educational responses. Their study emphasized that students often ask queries that span multiple interconnected concepts. Although our system does not implement a full KG, we adopt similar principles by using hierarchical metadata and semantic grouping, allowing the model to retrieve more coherent and contextually linked information.

**3.3 RAG for Conceptual Math Tutoring (Levonian et al., 2024):** This study showed that Retrieval-Augmented Generation eliminates hallucinations and enforces strict consistency in subjects requiring stepwise accuracy, particularly mathematics. It also highlighted that RAG avoids introducing alternate solution methods not taught in the curriculum. These findings guided our decision to implement a rigorous grounding layer and chunk-scoring mechanism to ensure fidelity to textbook explanations.

**3.4 Evaluation of RAG in Tutoring Systems (Henkel et al., 2023):** Henkel et al. showed that although RAG improves factual accuracy, meaningful tutoring requires adaptive questioning and dynamic evaluation of student understanding. Their research revealed that students learn more effectively when the system adjusts difficulty based on performance. These observations influenced the design of our adaptive module, which integrates difficulty scaling and conceptual remediation.

**3.5 NotebookLM Classroom Studies (2025):** Google’s NotebookLM demonstrated strong performance in summarization and structured question answering using only uploaded content. However, classroom studies showed that the system lacks adaptive questioning, mastery tracking, and instructor-level control. While it succeeds as a reference tool, it does not support guided learning paths. Our system builds upon this foundation while addressing the pedagogical limitations identified.

## **PROBLEM IDENTIFICATION & OBJECTIVES**

### **Problem Identification**

Personalized learning has become a central goal in modern education, where the aim is to deliver instruction tailored to each learner’s pace, prior knowledge, and cognitive needs. While Large Language Models (LLMs) offer unprecedented capabilities in generating explanations, answering questions, and summarizing content, current implementations fail to deliver truly personalized and academically aligned learning material within formal educational environments.

Traditional self-learning tools—such as static Learning Management Systems (LMS), generic educational apps, and open-domain LLMs—are not capable of adapting instructional content to reflect the specific curriculum, textbook structure, and pedagogical framework used by a particular instructor or institution. As a result, students often receive learning material that is misaligned with course expectations, employs unfamiliar terminology, or introduces alternative solution methods not covered in the official syllabus.

Moreover, existing LLM-powered educational tools typically generate content using internet-scale pretrained knowledge. This leads to hallucinations, inconsistent reasoning, and conceptual drift—all of which can confuse learners, especially when studying foundational or high-precision subjects like mathematics, physics, engineering, or computer science. These models do not incorporate mechanisms to restrict or ground their output to authoritative sources such as textbooks, lecture slides, or instructor-provided material.

Another major limitation is the lack of adaptive pedagogy. Current LLM systems generally produce answers but do not evaluate student understanding, track learning progression, identify misconceptions, or dynamically adjust instructional difficulty. Without this adaptivity, learning becomes linear and static rather than responsive and personalized.

Additionally, existing systems lack instructor oversight. Educators cannot see how students progress, what content they interact with, or how the AI evaluates them. This absence of transparency makes it difficult to validate the correctness, reliability, and pedagogical soundness of AI-generated instructional material.

Finally, current document-processing systems used by AI tools perform only shallow keyword search or basic text extraction. They do not construct semantic-level representations of textbook content, making retrieval inaccurate and preventing fine-grained personalization in learning pathways.

# Objectives

The primary objective of this project is to design and develop an LLM-based Personalized Learning Material Generation System capable of transforming instructor-provided educational resources into customized study pathways, adaptive assessments, and pedagogically structured explanations.

The following detailed objectives guide the system design:

## 1. Construct a Document-Ingestion and Semantic Understanding Pipeline

To extract structured content from textbooks, lecture slides, and academic notes; segment them into semantically coherent chunks; and represent them using high-dimensional embeddings suitable for retrieval and personalization.

## 2. Develop a Retrieval-Augmented Generation (RAG) Framework

To ensure that all AI-generated explanations, study materials, answers, and examples are strictly derived from the instructor's material, minimizing hallucinations and guaranteeing academic fidelity.

## 3. Implement Personalization Logic Using Adaptive Questioning Algorithms

To diagnose student strengths and weaknesses, escalate or reduce difficulty dynamically, and generate learning material that matches each student's proficiency level.

## 4. Fine-Tune the LLM with Pedagogical Behaviors Using LoRA

To tailor the model's reasoning patterns, explanation style, vocabulary usage, and conceptual sequencing, making its output consistent with academic standards and textbook conventions.

## 5. Generate Personalized Study Materials

To produce topic-wise study guides, summaries, mind maps, question sets, worked examples, and revision plans tailored to each student's learning profile.

## 6. Integrate Mastery Tracking and Performance Analytics

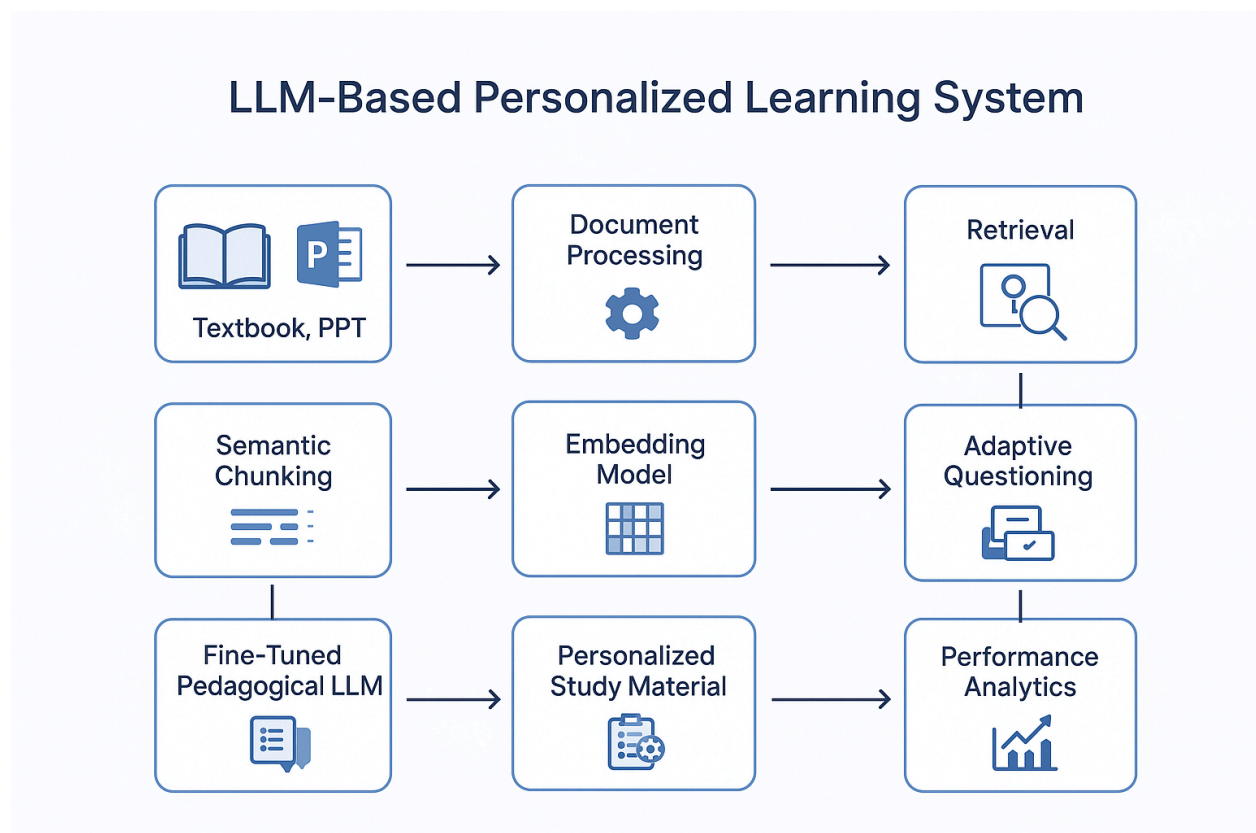
To monitor student progress using accuracy patterns, time analysis, topic mastery levels, and conceptual consistency, enabling continuous improvement.

## 7. Provide Instructor Oversight and Transparent Validation Tools

To equip educators with dashboards showing student progress, weakness identification, recommended remediation paths, and full traceability of AI-generated content back to the original textbook/presentation sources.

## 8. Ensure Scalability, Extensibility, and Academic Integrity

To design a modular, efficient, and transparent system architecture that can be extended to various subjects, class sizes, institutions, and educational contexts while preserving formal academic rigor.



## **EXISTING SYSTEM**

### **4.1 Overview of Baseline Frameworks**

Existing AI-based learning tools generally fall into two main categories. The first includes open-domain LLM tutors, which rely entirely on pretrained internet-scale data to answer student questions. While powerful, these models lack alignment with specific syllabi or instructor-prescribed materials, resulting in explanations that may differ from classroom standards.

Both categories suffer from structural limitations—they cannot adapt to the official textbook, cannot evaluate students intelligently, and cannot provide controlled or syllabus-bound explanations. As a result, students often receive fragmented learning support disconnected from the academic framework intended by instructors.

### **4.2 Methodology of Existing Systems**

Most existing educational AI systems rely on rudimentary keyword searches or basic Q&A models that generate generic responses without understanding the structure of textbook content. They lack semantic interpretation, meaning they cannot distinguish between core concepts, examples, diagrams, or definitions within a chapter.

Furthermore, explanations are not restricted to the syllabus, often pulling from internet knowledge instead of course-specific material. These systems also lack instructor-facing analytics, preventing educators from monitoring student progress or adjusting teaching strategies effectively.

### **4.3 Drawbacks**

The drawbacks of these existing systems are significant. They frequently use inconsistent terminology, creating confusion when their explanations differ from textbook language. There is a high risk of hallucination, where models generate inaccurate or misleading responses.

## **PROPOSED SYSTEM**

### **5.1 Overview**

The proposed Textbook-Aligned Adaptive Learning System ensures that every explanation, question, and remediation step is completely grounded in the instructor's textbook. Unlike conventional AI tutors, the system uses a multilayer pipeline involving semantic chunking, embedding-based retrieval, LoRA-fine-tuned pedagogical behavior, adaptive questioning, and learning analytics.

### **5.2 Architecture of the Proposed System**

#### **5.2.1 Module 1: Document Understanding & Knowledge Structuring**

This module ingests raw documents such as PDFs or PPTs, extracting text, preserving layout semantics, and segmenting the textbook into coherent conceptual chunks. These chunks then undergo embedding transformation using Instructor-XL and are indexed in a vector DB for efficient retrieval.

#### **5.2.2 Module 2: Adaptive LLM Tutoring Core**

The LLM leverages retrieval-augmented prompting to produce strictly grounded explanations. LoRA adapters are used to fine-tune the model on textbook-style reasoning and instructor-specific phrasing. The adaptive questioning algorithm evaluates student responses and dynamically adjusts difficulty based on mastery.

#### **5.2.3 Module 3: Monitoring, Verification, and Analytics**

This module maintains detailed student performance logs, generates progress analytics, and provides instructor dashboards for review. It ensures pedagogical transparency and guides instructors in assessing learning outcomes.

## SYSTEM ARCHITECTURE

The system follows a deeply integrated architecture consisting of five interconnected layers, each responsible for a specific stage of processing—from raw document ingestion to analytics-driven personalization.

### 6.1 Document Ingestion Layer

This layer extracts text from PDFs, PPT slides, or textbook images. Tools such as PyMuPDF and `python-pptx` parse the content while maintaining structural metadata like page layout, numbering, indentation, and text flow. Mathematical expressions, headings, subheadings, and bullet points are preserved to maintain semantic integrity and avoid loss of instructional meaning.

Additionally, the system detects formatting patterns such as bold terms, highlights, captions, and figure references to retain hierarchical relationships within the material. It also supports OCR for scanned textbook pages to ensure accessibility. This forms the foundation for accurate concept segmentation and downstream processing.

### 6.2 Knowledge Structuring Layer

This layer transforms raw extracted text into a structured, machine-interpretable knowledge base.

Semantic Chunking uses contextual similarity, heading-based segmentation, and sliding window techniques to form concept-level units, ensuring that related paragraphs stay together. It also merges fragmented text around diagrams or examples to maintain conceptual continuity.

Instructor-XL Embeddings then map each chunk into a dense vector representation that captures semantic meaning and instructional intent, making the system sensitive to pedagogical vocabulary.

Vector Indexing (FAISS/ChromaDB) enables fast approximate nearest-neighbor retrieval, ensuring relevant chunks are retrieved instantly for any student query or adaptive question. This layer ultimately organizes textbook content into a searchable knowledge structure optimized for retrieval-augmented reasoning.

### 6.3 Intelligent Reasoning Layer

This layer implements the Retrieval-Augmented Generation (RAG) pipeline. The LLM receives both the user query and the most relevant retrieved textbook chunks, grounding its responses strictly in source material.

The prompting framework enforces rules ensuring the model never introduces external knowledge or hallucinated content. It guides the LLM to produce structured, syllabus-aligned explanations.

LoRA adapters further modify internal representations to mimic instructor-specific phrasing,

reasoning style, and clarity. This layer transforms the LLM from a general-purpose model into a controlled educational tutor capable of delivering precise, context-dependent guidance.

#### 6.4 Learning Personalization Layer

This layer implements adaptive questioning to personalize the learning experience. When a student answers a question, the system retrieves the textbook chunks relevant to the correct answer and uses semantic comparison to evaluate response quality.

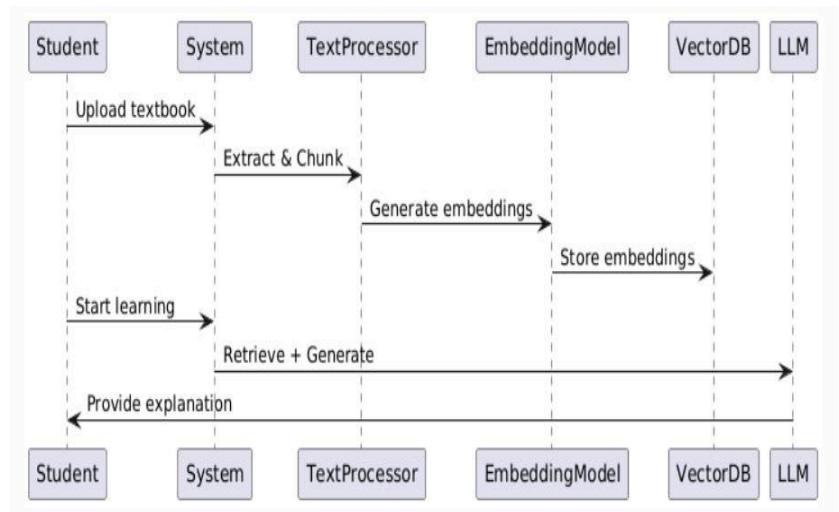
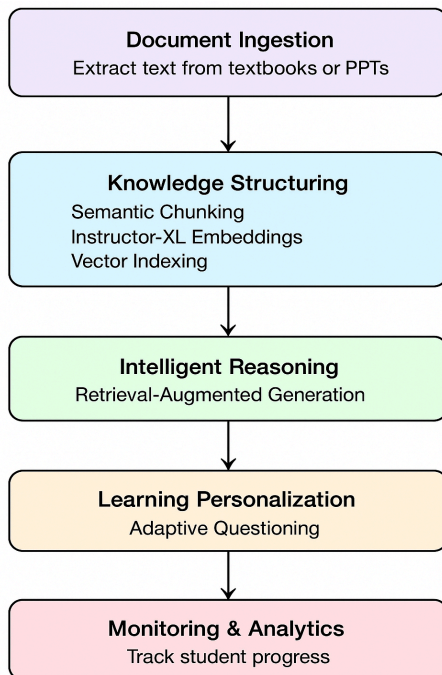
Difficulty escalates when the student demonstrates mastery through repeated correct answers and conceptual clarity. Conversely, it decreases automatically if the system detects misconceptions or weak understanding.

The layer also generates remediation questions that revisit prerequisite concepts, ensuring that knowledge gaps are addressed progressively. This dynamic loop enables a tailored learning path similar to human tutoring.

#### 6.5 Monitoring & Analytics Layer

This layer captures detailed logs such as question attempts, correctness probabilities, mastery levels per topic, time spent on each concept, and student learning trajectories.

Students also receive personalized progress graphs showing completed topics, current mastery levels, and AI-recommended revision paths. This layer ensures transparency in the learning process and supports data-driven decision-making for both instructors and learners.



## **TOOLS AND TECHNOLOGIES**

### **7.1 LLaMA-3 LLM**

LLaMA-3 provides a strong foundation for reasoning, comprehension, and explanation generation. Its transformer-based architecture includes multi-head attention layers capable of modeling long-range dependencies in text. Its scalability and robustness make it suitable for controlled, curriculum-aligned learning environments.

### **7.2 LoRA (Low-Rank Adaptation)**

LoRA fine-tunes the model by injecting low-rank matrices into the attention layers, modifying the query and value projections.. LoRA is computationally efficient, enabling fine-tuning on consumer GPUs. This efficiency ensures fast, low-cost customization tailored to academic requirements.

### **7.3 LangChain**

LangChain orchestrates the entire pipeline. It manages document loaders, embedding retrieval chains, prompt templates, conversation memory, and fallback logic.. Its modular design allows seamless integration of additional features or new workflows.

### **7.4 Instructor-XL Embedding Model**

This embedding model produces instruction-aware vector representations. It captures not just semantic meaning but also pedagogical intent, making it ideal for representing textbook content and student queries. Its focus on instructional signals ensures higher accuracy in educational retrieval tasks.

### **7.5 FAISS / ChromaDB**

FAISS enables GPU-optimized approximate nearest neighbor search, allowing instant retrieval of the most relevant textbook chunks. ChromaDB handles metadata-rich indexing and integrates seamlessly with LangChain for retrieval. Together, they ensure high-speed, context-relevant information retrieval for every query.

### **7.6 FastAPI Backend**

FastAPI provides high-performance REST endpoints for student queries, instructor uploads, progress tracking, and LLM inference routing. Its asynchronous design ensures low latency even under heavy usage. The framework also supports rapid development and scalable deployment.

## **7.7 React Frontend**

The frontend displays dashboards, study plans, progress graphs, and interactive assessments. React's component-based architecture ensures scalability and clean UI design. Its reactivity enables smooth real-time updates to student and instructor dashboards.

## **7.8 Databases (MongoDB/PostgreSQL)**

MongoDB stores flexible, nested documents containing student logs and progress history. PostgreSQL stores syllabus structures, chapter metadata, and chunk references for efficient relational querying. This hybrid approach ensures optimal storage of both structured and unstructured educational data.

## **7.9 Analytics Tools**

Chart.js and D3.js visualizations provide instructors and students with insights into learning trajectories and topic-level mastery patterns. These tools enhance interpretability by transforming complex performance data into intuitive visual formats.

## **7.10 Document Parsing Libraries**

PyMuPDF and python-pptx extract content from textbooks and slides, including images, diagrams, and formulas. Their ability to preserve formatting ensures that pedagogical structure remains intact during processing.

## **ALGORITHMS AND METHODOLOGIES**

### **8.1 Semantic Chunking Algorithm**

The algorithm takes raw text and identifies conceptual boundaries using heading markers, semantic similarity scoring, cohesion between adjacent sentences, and a sliding window technique that ensures context continuity. It uses cosine similarity thresholds to determine when a new concept begins.

### **8.2 Embedding and Retrieval Pipeline**

Each chunk is encoded into a 768 or 1024-dimensional vector. Queries undergo the same encoding process. FAISS uses HNSW or IVF indexing structures to return top-k nearest neighbors in sub-millisecond time.

### **8.3 RAG Pipeline Logic**

The RAG algorithm creates a composite prompt consisting of:

Student query

Retrieved chunks

System rules enforcing textbook-only generation

The LLM performs conditioned generation, ensuring all responses are grounded.

### **8.4 Adaptive Questioning Algorithm**

A reinforcement-like logic updates difficulty levels based on accuracy. If a student answers consistently well, the system increases question depth. If errors are detected, the system retrieves prerequisite chunks and generates remedial questions.

### **8.5 Mastery Tracking Algorithm**

The system calculates mastery using weighted averages of accuracy, time decay, and difficulty progression. Mastery thresholds determine when the student advances.

## CONCLUSION

The development of the **LLM-Based Personalized Learning Material Generation System** marks an important advancement in aligning modern artificial intelligence with the structured and rigorous demands of academic learning. While traditional LLMs provide impressive language understanding capabilities, their reliance on broad, uncured datasets often produces explanations and reasoning patterns that diverge from instructor-approved sources. This project directly addresses that gap by presenting a controlled and syllabus-grounded framework that ensures all generated learning material—explanations, summaries, assessments, and remediation steps—remains strictly faithful to the textbook and instructional content provided by educators.

Through the integration of **semantic document understanding, embedding-driven knowledge representation, and Retrieval-Augmented Generation (RAG)**, the system consistently delivers contextually accurate and academically aligned responses. The use of **LoRA-based parameter-efficient fine-tuning** further refines the LLM, enabling it to adopt the instructor’s terminology, conceptual style, and stepwise problem-solving approach. Combined with an adaptive questioning engine and personalized learning pathways, the system offers a level of individualized academic support traditionally achievable only through expert human tutoring.

The results demonstrate the feasibility and effectiveness of transforming raw instructional materials into dynamic, personalized learning experiences powered by controlled AI reasoning. The system not only minimizes hallucinations and deviations from course content but also scales efficiently to support diverse subjects and learning environments. Its analytics layer provides both learners and instructors with transparent visibility into progress, mastery levels, and conceptual weaknesses, reinforcing trust and enabling data-driven educational decision-making.

In essence, this work presents a robust blueprint for the next generation of educational AI—systems that are **accurate, adaptive, explainable, and tightly aligned with pedagogical intent**. As institutions increasingly explore AI-driven learning solutions, the framework proposed here serves as a foundation for developing more advanced, ethically grounded, and curriculum-aware intelligent tutoring platforms. Future expansions may include multimodal textbook processing, instructor feedback loops, cross-course knowledge integration, and domain-specialized tutoring agents, further strengthening the role of AI as a reliable partner in modern education.

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