LectūraAgents: A Multi-Agent Framework for Adaptive Personalized AI-Assisted Learning and Embodied Teaching

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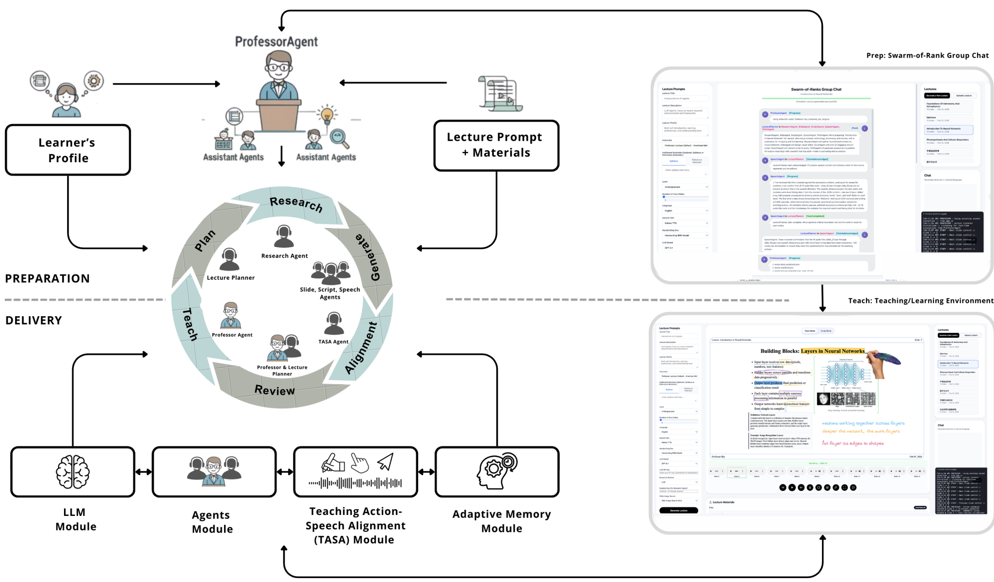

Figure 1: Overview of LectūraAgents: a hierarchical multi-agent framework for end-to-end adaptive personalized learning experiences. Given a lecture prompt or learning materials and a learner profile, a *ProfessorAgent* leads a collaborative team of specialized agents through research, planning, design, evaluation and embodied delivery of lecture and study contents that adapt to the individual learner. The framework provides students with access to real-time adaptive, personalized teaching and study sessions.

Abstract

Effective personalized AI-assisted learning demands learning systems that can not only generate accurate learner-specific educational materials, but also dynamically adapt their instruction to diverse learners. However, existing educational agent frameworks have primarily focused on lecture content automation and simulations, which often fall short of modelling multimodal and embodied instructional methods tailored for the individual learner. To this end, we propose LectūraAgents—a multi-agent framework that enables personalized learning through end-to-end adaptive embodied teaching. At its core, LectūraAgents mirrors a professor-student relationship, in which the *ProfessorAgent* leads a collaborative team of specialized subordinate agents through research, planning, review, and embodied delivery of lecture contents that adapt to a learner's needs. The framework offers three main contributions: (1) a hierarchical multi-agent architecture for end-to-end personalized learning; (2) an adaptive embodied teaching mechanism, wherein the *ProfessorAgent* executes visible and pedagogically motivated teaching actions (*e.g.*, handwrite, highlight, underline, etc.) over contents in a teaching environment while speaking; and (3) a Teaching Action-Speech Alignment (TASA) algorithm that employs salience-based heuristics and temporal semantic segmentation to generate coherent teaching action sequences aligned with learner profiles. We evaluate LectūraAgents on diverse courses at high school, undergraduate, and graduate levels using sample-specific rubric-based analysis; with generated lecture materials and teaching actions assessed and validated by expert educators. Experimental results show consistent gains in lecture content quality, embodied teaching quality, assessment, and personalization over existing approaches, positioning LectūraAgents as a pedagogically well-grounded framework for personalized learning at scale.

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The dataset for this work is available at: https://huggingface.co/datasets/Jaward/lectura-agents-data.

1 Introduction

Adaptive personalized AI-assisted learning has emerged as a promising approach for tailoring instructions to individual learners, with studies reporting gains in motivation, engagement, and learning outcomes, especially in online educational settings [1–3]. However, contemporary personalized learning solutions and frameworks typically focus on adapting what is recommended, rather than how instructional content is delivered to the learner [4]. Research on embodied teaching shows that performing teaching actions (*e.g.*, writing, pointing or gesturing) during a lecture can help guide attention, foster conceptual understanding, and enhance overall learning outcomes [5–7]. These findings point to the need for personalized learning solutions that well integrate adaptive learning contents with embodied instructional delivery.

Recent frontier models demonstrate strong reasoning and agentic capabilities that have enabled planning, tool-use, and multi-step problem solving, opening new possibilities for applications in personalized learning [8–11]. This breakthrough has led to the exploration of LLM-powered agent frameworks for education, where specialized agents automate learning and teaching tasks to support students and educators [12]. Moreover, recent efforts have further demonstrated the potential of leveraging multiple agents to act as personal tutors and learning companions that provide on-demand teaching and learning support based on individual needs [13–16].

However, the predominant focus of most related frameworks has been on simulations, where agents enact roles in virtual classrooms [17–19] simulate teacher–student dialogues to evaluate teaching behaviors and feedback strategies [20, 21], or coordinate agent workflows for generating personalized learning materials [22, 23]. These are important proof of concepts, but their impact is limited to controlled virtual environments that do not capture the myriad nuances of adaptive personalized learning in real life scenarios. Other works have explored single-agent or prompt-engineered LLM tutoring systems [24–26] that generate explanations, feedback, or instructional contents, but without rigorous review or modeling of how such contents should be contextualized and adapted to diverse learning profiles. Few related works extend beyond these scopes to adopt a broader personalized instructional perspective that is often centered on automating course content generation [27, 28], which is primarily delivered in text-only modality, with no account for personalized embodied instructional delivery. Collectively, these systems offer valuable contributions to AI-assisted learning but remain fragmented in scope, lacking a unified model that connects personalized content generation with adaptive embodied delivery. Consequently, key pedagogical features, including coordinated lesson planning, iterative content review, embodied teaching, and alignment between teaching behaviour and learner needs, remain insufficiently addressed.

To address these limitations, we propose LectūraAgents, a hierarchical multi-agent framework for end-to-end personalized lecture generation and embodied lecture delivery. Our framework moves beyond simulations and static content generation, to managing the entire life cycle of a lecture (*i.e.*, from preparation to delivery, as shown in Figure 1), while adapting to individual learning preferences. LectūraAgents offers three primary contributions:

1. **A hierarchical multi-agent architecture for end-to-end personalized learning:** we propose the first multi-agent framework with end-to-end personalization for learning. It mirrors a professor–student relationship, where a ProfessorAgent coordinates specialized assistant agents (at different hierarchies) to plan, research, review, and create lecture contents tailored for the individual learner.
2. **A Teaching Action-Speech Alignment (TASA) algorithm:** a novel technique that uses LLM-based semantic analysis, temporal content segmentation, and salient heuristics to accurately align relevant teaching actions to regions or contents in a teaching environment (*e.g.*, over a slide).
3. **An embodied lecture delivery mechanism:** our framework enables a ProfessorAgent to perform visible, interpretable teaching actions (*e.g.*, highlight, handwrite, underline, etc.) directly over contents in the teaching environment (in our case, lecture slides) with a clear pedagogical rationale for each action taken.

LectūraAgents decomposes personalized instruction into agents operating at three hierarchies across two sessions: **Lecture Preparation** and **Lecture Delivery**. In the preparation session, the *ProfessorAgent* leads a team of validator and executor agents through planning, research, generation, and evaluation of lecture artifacts. During the delivery or teaching session, the *ProfessorAgent* utilizes these artifacts to enact an embodied teaching role, executing visible and pedagogically motivated teaching actions on contents in the learning environment.

We conducted extensive evaluations of the framework on diverse courses at high school, undergraduate, and graduate levels, assessing lecture quality, teaching quality and personalization. Our experiments show that LectūraAgents can produce high quality lecture artifacts, while effectively adapting personalized teaching strategies to diverse learner profiles through coherent embodied teaching action sequences.

2 Related Work

2.1 Adaptive Personalized AI-Assisted Learning

The idea of personalized learning predates LLMs and LLM agents. Early theories of memory, such as Atkinson and Shiffrin's model of how information is encoded and rehearsed [39] and Cowan's account of short-term and long-term memory capacities [40], helped establish the cognitive foundations for adapting instruction to the ways learners process and retain information. These insights inspired models of personalized learning that emphasized learner-centered pathways, individualized pacing and tailored support. Before LLMs became widely adopted, deep learning models were used in intelligent tutoring systems (ITS) to monitor learners' performances, adjust task difficulty, and deliver personalized feedback [41–43]. Reviews show that AI-assisted personalized learning has a positive impact on students' engagement and learning outcome across diverse learning settings [44–46]. More recent empirical studies of AI-driven adaptive platforms in university and language-learning contexts, report gains across performance, satisfaction, and self-directed learning [47–49]. Collectively, these findings make clear the significance of adaptive personalized learning, forming the foundations upon which our framework is built.

Table 1: Comparison of LectūraAgents with existing multi-agent frameworks in this domain

Framework	Teaching Modality	Embodied Agent(s)	Teaching Action Alignment	Personalization	Multi-Agent Collaboration
EduAgent [29]	Text	✗	✗	✗	✗
Agent4Edu [30]	Text (simulation)	✗	✗	✓	✓
EducationQ [31]	Text (simulation)	✗	✗	✗	✗
FACET [32]	Text	✗	✗	✓	✗
KELE [33]	Text	✗	✗	✗	✗
Instructional Agents [34]	Text	✗	✗	✗	✓
EduPlanner [35]	Text	✗	✗	✓	✓
GenMentor [36]	Text	✗	✗	✓	✓
SimClass [37]	Text (simulation)	✗	✗	✓	✓
WikiHowAgent [38]	Text	✗	✗	✗	✓
LectūraAgents	**Multimodal (Embodied)**	✓	✓	✓	✓

2.2 LLM Agent Frameworks for Education

Early works on LLM agents demonstrated how language models can plan, use tools, decompose tasks, and coordinate multi-step reasoning across multiple collaborating agents [50–53]. These abilities soon inspired educational multi-agent frameworks [54]. For instance, EduAgent [29] models diverse student personas using cognitive-science priors, Agent4Edu [30] simulates learner responses with memory-based generative agents, and EducationQ [31] stages multi-agent teacher-student-evaluator interactions to assess teaching behaviours. Similarly, systems like SimClass [37] and WikiHowAgent [38] extend simulation to classroom dynamics and procedural learning. Course-content automation then became a focus, with Instructional Agents [34] generating full course materials through role-based collaboration, and EduPlanner [35] iteratively refining lesson plans via evaluator–optimizer agent loops. More recent works have also introduced personalization: FACET [32] creates learner-adapted worksheets, KELE [33] provides concept-level enrichment and feedback, and GenMentor [36] builds personalized learning paths from learner goals. While these contributions demonstrate how multi-agent systems can enhance learning, they lack relevant capabilities (as summarized in Table 1) that integrates personalized content generation with embodied instructional delivery.

2.3 Embodied Teaching Agents

Embodied teaching in digital settings refers to instructional methods that combine verbal instruction with spatial teaching actions (*e.g.*, writing, highlighting, underlining, or pointing) over learning contents in a virtual teaching environment. These actions help guide attention, reduce cognitive load, and support concept formation [55, 56]. Earlier models like AutoTutor and its variations [57, 58] demonstrated the benefit of animated pedagogical agents capable of conversational scaffolding. Recent systems have explored programmatic video-based approaches, for example, Xu et al. [59] explored how AI-generated lecture videos compare with real lectures, while AutoLectures [60] converts slides into narrated videos with highlight actions (using Levenshtein and LLM-based matching), and PASS [61] automated slide and speech generation from word documents. These efforts emphasize the importance of action-based instructional cues, but fall short of delivering a coherent end-to-end personalized, adaptive, and pedagogically informed embodied instruction.

3 LectūraAgents

We designed LectūraAgents to be both domain-specific and extensible given the nature of the problem we are trying to solve. Its framework integrates planning, research, and pedagogical embodiment within a cohesive, end-to-end hierarchical architecture that supports both personalization and continual learning in tandem. LectūraAgents consists of four interconnected modules:

- **LLM** – The LLM module provides agents with access to frontier models (*e.g.*, GPT-5, Gemini 3 pro, Claude Sonnet 4, Deepseek V3.2, Qwen 3, and Kokoro TTS [62]) through their respective custom APIs. It serves as the brain behind agents, handling text, image, and speech modalities.
- **Agent** – This module holds the core logic for each agent's role, capabilities, and tools. It also enables coordinated multi-agent collaboration through dynamically invoked actions for assigned tasks. The framework adopts a three-tier hierarchical collaborative mechanism with a lead coordinator agent managing a validator agent, who in turn manages executor agents for lecture content generation. To complete tasks, agents execute a series of actions utilizing custom tools.
- **TASA** – The Teaching Action-Speech Alignment (TASA) module handles alignment between embodied teaching actions and their corresponding lecture speeches. It provides logic for salient heuristic analysis and temporal semantic segmentation, which help provide context when curating relevant teaching action sequences.
- **Memory** – This module implements short-term, long-term, and dynamic memories, which together allow agents to preserve context, track learner needs, and adapt their behaviour over time.

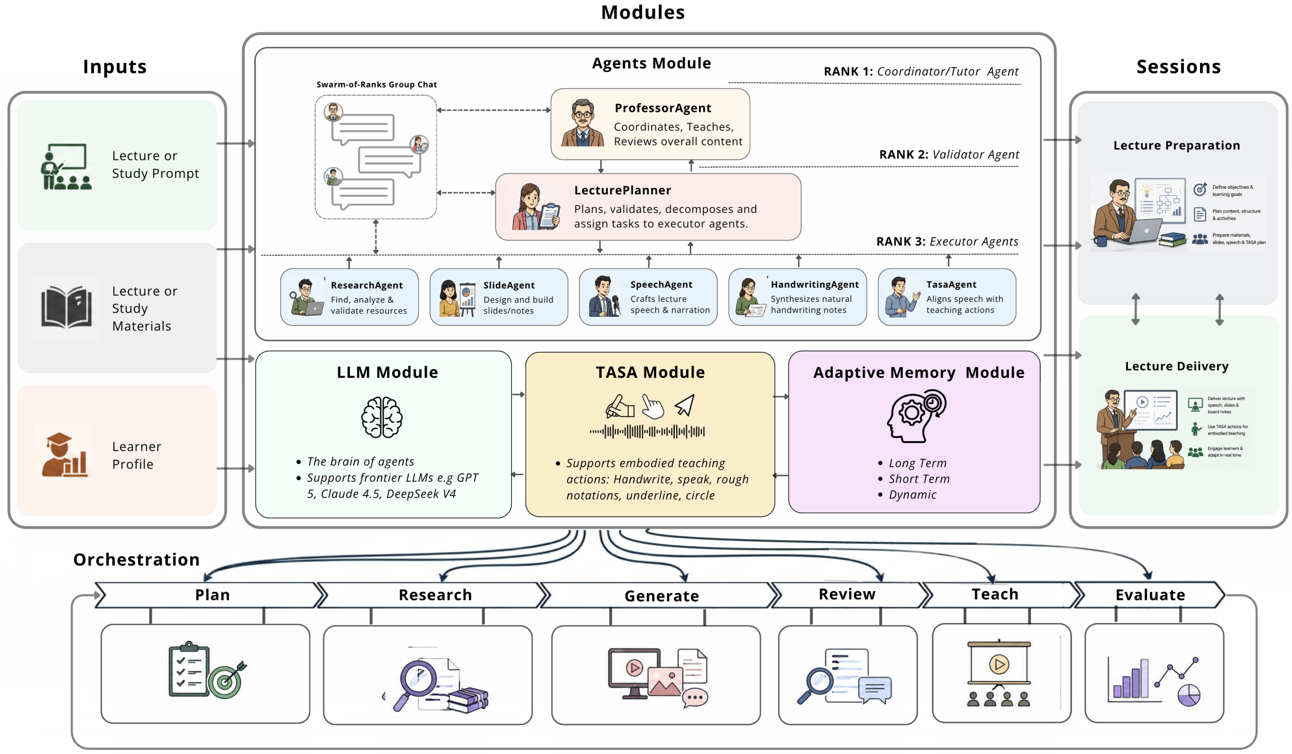

Figure 2: LectūraAgents Architecture. The framework adopts a hierarchical multi-agent architecture, modeled after a professor–students' relationship. One in which a coordinator agent (or *ProfessorAgent*) guides a collaborative team of validator and executor agents through planning, research, design, and delivery of personalized lecture contents. Multi-agent collaboration is mediated through an orchestration layer with group-chat communication that enables iterative planning, self-evaluation, and continuous refinement of generated materials. This architecture is supported by four interconnected modules: Agents, LLM, TASA, and Adaptive Memory.

These four modules span across the framework's two main stages: *Lecture Preparation Session* and *Lecture Delivery Session*. Moreover, as shown in Figure 3, the delivery session supports two modes: *Teach Mode*, which generates a new personalized lecture based on the learner's profile and provided learning materials, and *Study Mode*, which allows learners to upload existing materials, such as notes, books or projects, and interact with the *ProfessorAgent* through real-time Q&A.

3.1 Lecture Preparation Session

In this stage, the *ProfessorAgent* leads a collaborative team of specialized agents through planning, research, alignment, review, and creation of personalized lecture artifacts (*e.g.*, lecture plan, slides, scripts, speech, teaching actions, notes, etc.). A quick overview of the entire process can be found in Algorithm 1.

Lecture Prompts and Configs. Lecture preparation begins by processing the learner's prompts along with a range of configuration choices that define the scope, style, and preferences of the lecture. The prompt captures the lecture topic, its intended coverage, and the learner profile, so the framework can adapt content depth and learning preferences, while optional syllabus or reference materials help anchor the lecture to a course context or source material. Additional settings specify the instructor persona, target academic level (high school, undergraduate, masters, or PhD), language of instruction (which currently includes English, Chinese, French, or Spanish), and the approximate number of slides to be generated. Learners can also choose their preferred voice model, handwriting mode (either Handwriting RNN Model or Preset Font Handwriting), LLM model, and *research* method (using Wikipedia or Google search). Together, these inputs provide the initial conditions that guide downstream multi-agent collaboration, planning, research, content generation, and embodied teaching. Our teaching and learning environment can be accessed via a browser (as shown in Figure 3) for easier entry of all inputs. Additional details on lecture prompts and configurations can be found in Appendix B.

Multi-agent Collaboration. When a lecture is prompted, the *ProfessorAgent* first initiates the preparation session, creating a collaborative group chat named *Swarm-of-Ranks Group Chat* (shown in Figure 4) – where agents at different ranks collaborate to complete assigned tasks. In this group chat we have a coordinator (*ProfessorAgent*), a validator (*LecturePlanner*), and different executor (*ResearchAgent, SlideAgent, ScriptAgent, SpeechAgent,* and *Teaching Action-Speech Alignment agent* or *TasaAgent*) agents. The coordinator agent (Rank 1) supervises the validator agent (Rank 2), who in turn manages executor agents at Rank 3. This hierarchical structure allows for efficient review and successful completion of

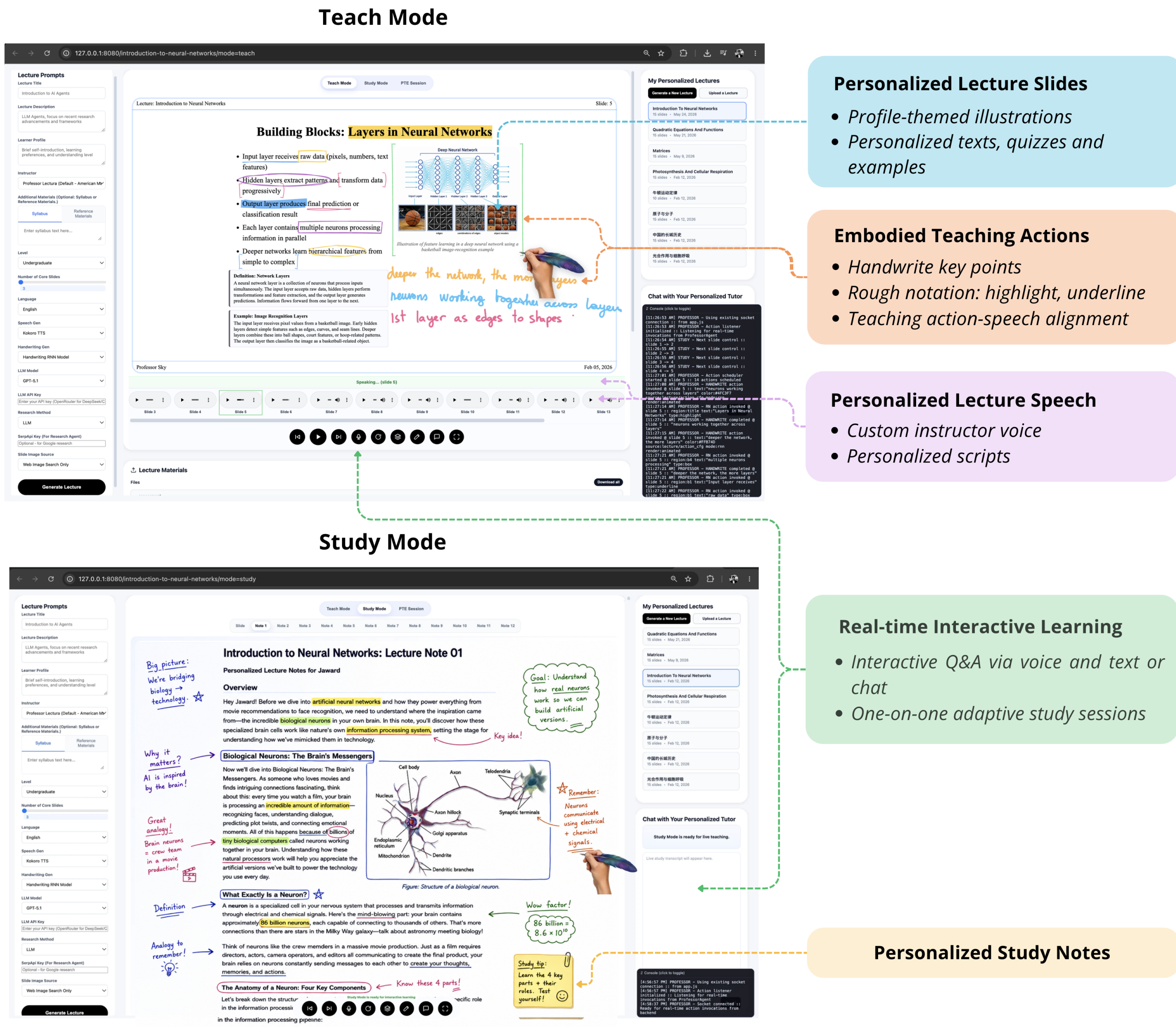

Figure 3: An example of adaptive personalized learning experience with LectūraAgents

assigned tasks. Agents communicate by sending messages in the group chat through a communication layer. There are nine message types: [Task], [TaskAcknowledged], [Progress], [TaskCompleted], [Approval], [Revisal], [Handoff], [RevisalSucceeded], and [Revisal-Failed]. Table 2 shows the message-types respective agents can send in the group chat.

Table 2: Message types for respective agents at different ranks

Rank(s)	Message Types	Agents
1, 2	[Task], [Approval], [Revisal]	*ProfessorAgent* and *LecturePlanner*
1, 2, 3	[TaskAcknowledged], [Progress], [TaskCompleted]	All agents
3	[Handoff], [RevisalSucceeded], [RevisalFailed]	*ResearchAgent, SlideAgent, ScriptAgent, SpeechAgent, TasaAgent*

Planning. The lecture preparation process starts with planning, wherein the *ProfessorAgent* instructs the *LecturePlanner* to draft a lecture plan based on the requested lecture topic and learner profile. The *LecturePlanner* first conducts preliminary research on the topic, then writes a detailed plan, and submits it for review and approval by the *ProfessorAgent*. The plan contains lecture metadata, learner profile, and detailed descriptions of tasks for each executor agent with respective criteria for completing assigned tasks. Once the plan is approved, the *LecturePlanner* then instructs and coordinates executor agents to generate lecture contents based on the plan. Subsequent preparation stages will involve sequential execution of tasks by executor agents and iterative validation by the *LecturePlanner*.

Generation. This stage starts with the *SlideAgent*, which is tasked with designing each slide (in HTML format), using a custom slide builder tool, and generating respective contents based on structural and pedagogical criteria from the lecture plan. Each slide is designed to support contents in text, image, video, and speech modalities, via structured content blocks. Slide images can be either generated or sourced online via web search. Next, the *ScriptAgent* utilizes the generated slide contents (along with lecture plan and research findings) to create a personalized and pedagogically informed script for each created slide. Scripts are conditioned to capture the learner's attention, level of understanding, and learning preferences. Finally, the scripts are then passed on to the *SpeechAgent* which performs speech synthesis, converts scripts to speech (in the learner's desired instructor voice), and creates word-level timestamps for each speech action using Whisper ASR [63]. These artifacts will later be used during alignment and review.

Alignment. Given the generated speech timestamps, scripts, slide contents, and learner profile, the *TasaAgent* first performs a preliminary teaching action analysis using segmentation and salient heuristic tools in the TASA module. This analysis starts with the temporal semantic segmentation of slide contents and scripts to identify segments that should receive teaching actions; it then applies salience-based heuristics to provide rationale for each teaching action application.

Currently, LectūraAgents supports two kinds of teaching actions: Rough Notation (RN), *e.g.*, highlight, underline, circle, box, etc., and Handwriting actions (HW), *i.e.*, writing down key points in natural human-like handwriting style, while speaking. This analysis results are then added to the agent's context when mapping pedagogical teaching actions to contents in the slide teaching environment. The *ProfessorAgent* will later utilize the resulting teaching action sequences during embodied teaching in the lecture delivery session.

Self-reflection. In addition to the hierarchical review mechanism present in multi-agent collaboration, we ensure each agent self-reflects on any completed tasks to find and fix issues before submitting results for review by the validator agent. They do this by first reviewing completed tasks, then self-validating them against required criteria detailed in the lecture plan.

Personalization. We ensure personalization across all generated lecture contents—slides, images, quizzes, lecture notes, scripts and teaching actions—by conditioning generation on the learner's profile, learning preferences, and usage history in memory. For example, slide contents, as shown in Figure 5, are adapted to the learner's interests by framing concepts around a favourite sport or hobby, or can be tailored into an easier-to-follow learning path (*e.g.*, more scaffolding or simpler analogies) when the student profile indicates lower prior knowledge. Slide images are generated

Algorithm 1 Lecture Preparation Session

Input: Lecture Prompt L_P, Learner Profile U
Parameters: Coordinator/validator agents $\{A_P, A_{LP}\}$; executor agents $E_A = \{A_R, A_S, A_{Sc}, A_{Sp}, A_T\}$; preparation plan $P = \{P_1, P_2, \ldots, P_n\}$; adaptive memory $M_A = \{M_s, M_L, M_d\}$; Swarm-of-Ranks group chat G_{chat}
Output: Lecture artifacts L_A = {Plan, Slides, Script, Speech, TeachingActions, Notes, Assessments}

```
Initialize memory {M_s, M_L, M_d} and agents {A_P, A_LP}
A_P starts prep session and instantiates G_chat
A_P debriefs A_LP and requests lecture plan P
repeat
    A_LP drafts P from (L_P, U) → M_d
    A_P reviews P and gives feedback → M_s
    A_LP updates P based on feedback → M_d
until A_P approves P or max iterations reached
Initialize executor agents E_A
for each P_i in P do
    A_LP debriefs E_A on assigned tasks
    for each executor E_i in E_A do
        repeat
            E_i plans and executes task
            E_i self-reflects and submits
            A_LP reviews task and gives feedback
        until A_LP approves task or max iterations reached
    end for
end for
A_LP submits artifacts L_A for final review by A_P
A_P reviews and validates L_A
return L_A
```

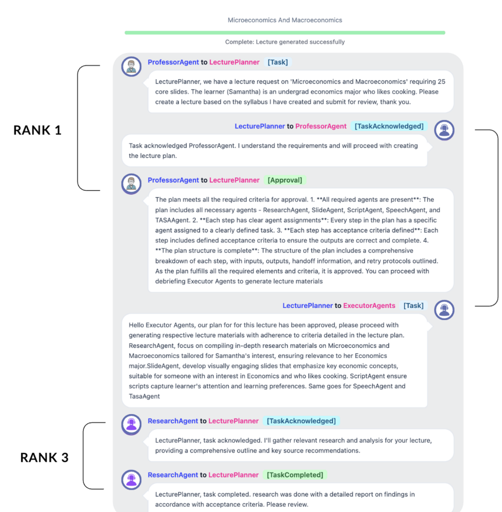

Figure 4: Swarm-of-Ranks group chat

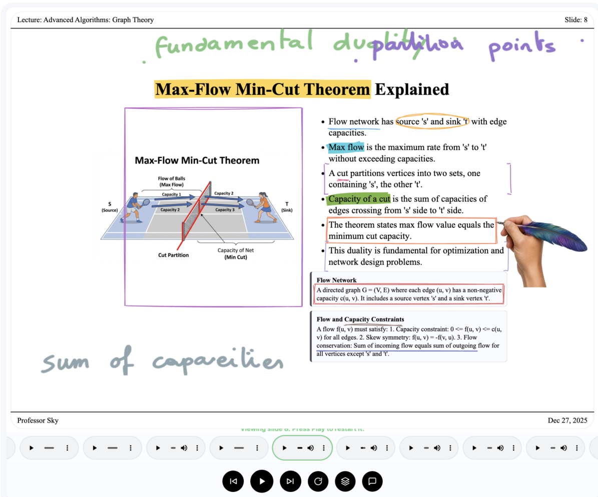

Figure 5: Screenshot of a personalized slide for an undergraduate student whose favorite sport is tennis, with key concepts explained using tennis-themed visuals and embodied teaching actions over slide contents.

to match the same themes and difficulty level, while quizzes are personalized in both content and phrasing to assess understanding using familiar scenarios. The resulting notes, scripts, and teaching actions mirror these choices to ensure a coherent, learner-specific narrative throughout the lecture.

Review. Finally in this session, generated lecture artifacts are assembled by the *LecturePlanner* and submitted to the *ProfessorAgent* for final review. During review the *ProfessorAgent* again validates lecture artifacts based on lecture content quality, teaching quality, action alignment, and personalization. Once review is successful, the *ProfessorAgent* agent then takes on the role of teacher in the subsequent lecture delivery session.

3.2 Lecture Delivery Session

During this stage, the *ProfessorAgent* assumes the role of an embodied instructor that executes pedagogical teaching actions in the slide environment using lecture artifacts from the lecture preparation session. In this work, we define a ***Teaching Action*** as a semantically bounded, visually interpretable and pedagogically motivated operation performed by the *ProfessorAgent* over contents in the teaching environment, while speaking. Each action comes with a rationale for why it was taken at a particular time. We experiment with two types of teaching actions:

1. **Rough Notations (RN):** These are actions that involve marking or emphasizing existing contents on the slide. Examples include highlighting key terms, underlining important phrases, circling diagrams, or boxing critical points. RN actions are used to draw the learner's attention to specific areas of the slide that are relevant to the current topic being discussed. For improved user experience, we make use of a hand-drawn annotation library [64] that simulates human-like rough notations for these actions.
2. **Handwriting (HW):** These actions involve writing new information directly onto the slide canvas in a natural, human-like handwriting style. This can include jotting down definitions, drawing diagrams, or annotating existing content. HW actions serve to reinforce learning by actively engaging the learner with newly introduced concepts during the lecture. We utilize both a handwriting recurrent neural network model based on Graves [65] and a preset font-based handwriting synthesis for this teaching action.

These actions undergo preliminary review, analysis, and alignment using our proposed Teaching Action-Speech Alignment (TASA) algorithm, summarized in Algorithm 2.

Teaching Action–Speech Alignment (TASA) Algorithm. TASA uses a combination of LLM-based salience heuristics analysis and temporal semantic segmentation to help guide the *TasaAgent* with prospective relevant teaching action sequences. The agent's objective is to emit an ordered list of pedagogically informed teaching action-speech sequences $AS_{\text{seq}} = \{S_1[a_1, a_2, \ldots, a_n], \ldots, S_n[a_1, a_2, \ldots, a_n]\}$, for each slide S_n, where each action a_n is given by:

$$a_n = \{\text{actiontype}_n, \text{start}_n, \text{end}_n, \text{cfg}_n\} \tag{1}$$

$actiontype_n$ can be either RN or HW, $(start_n, end_n)$ gives the duration for the action, and cfg_n holds additional metadata or configuration specific to the action type, as illustrated in Figure 6.

Figure 6: Data structure for Rough Notation and Handwriting teaching actions in json.

Temporal Semantic Segmentation. Before performing salience heuristics analysis, we first segment slide contents and speech semantically (see Figure 7), in order to augment our agent's context for better teaching action sequences. Segment labels include *Pedagogical, Personalized, Salient, Adaptive*, and *Assessment*, each of which helps provide insight into the kind of teaching actions to apply. For each slide region $region_n \in R_s$ and corresponding speech segment with label $label_n$, the TasaAgent creates a segment $segment_n$ given by:

$$\text{segment}_n = \{\text{label}_n, \text{region}_n, \text{speech\_segment}_n\} \tag{2}$$

specifically, for each candidate segment $segment_n$ in a slide S_n, TASA analyses the segment data and assigns a suitable teaching action along with a rationale r_n in natural language, explaining why this action is appropriate for that specific region. The final heuristics analysis data for a given slide is recorded as:

$$\mathcal{H}(S_n) = \{\text{segment}_n, a_n, r_n\} \tag{3}$$

which provides the *TasaAgent* with a structured context when generating the resulting teaching action-speech sequences AS_{seq}.

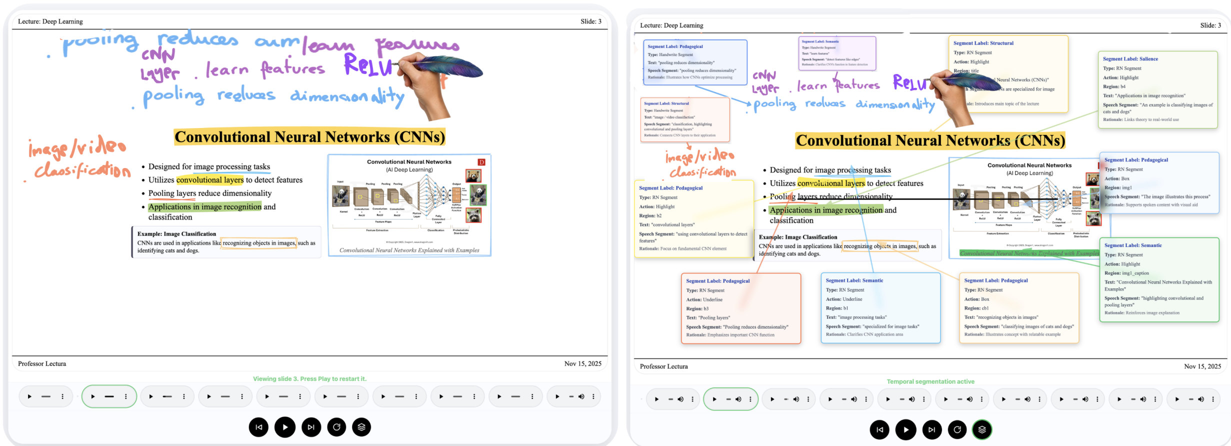

Figure 7: The left slide shows already taken RN and HW teaching actions on a slide, while the right slide shows temporal semantic segmentation of slide contents with segment labels, action types, rationales, regions and their respective speech and script segments.

Embodied Teaching. Given the generated teaching action-speech sequences, the *ProfessorAgent* dynamically schedules and invokes respective teaching action functions over regions in the slide environment (in sequence), while speaking. Each action function is tied to a specific speech segment (with word-level timestamps) and applies a targeted visual operation such as handwriting, highlighting, circling, or underlining, directly on the corresponding slide region, as illustrated in Figure 8.

To ensure accurate and realistic embodiment, the agent is provided with a discrete world view of the slide environment and its contents, while using a 3D quill-holding hand to execute the embodied teaching actions with precise spatial targeting of regions and their corresponding action types. As a result, embodied teaching actions like handwriting, highlighting, circling, etc., are executed in a natural, interpretable, and pedagogically grounded manner that closely mirrors human instructional behaviour.

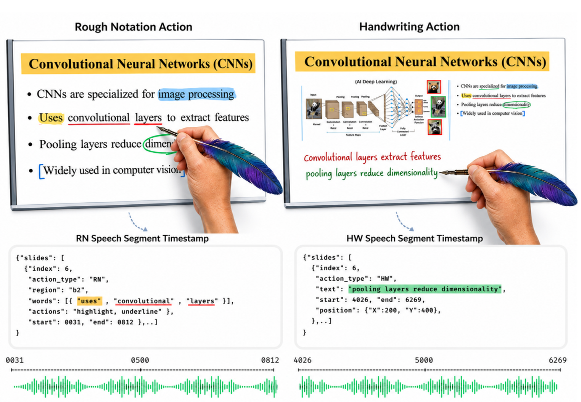

Figure 8: Illustration of Embodied Teaching in LectūraAgents

Algorithm 2 Teaching Action-Speech Alignment (TASA) Algorithm

Input: Slides $S = \{S_1, S_2, \ldots, S_n\}$, scripts $S_c = \{S_{c1}, S_{c2}, \ldots, S_{cn}\}$, word-level speech timestamps T_d, learner profile U

Parameters: *TasaAgent*, regions R, labels {Pedagogical, Personalized, Salient, Adaptive, Assessment}; RN and HW action types, salience data $\mathcal{H}$, dynamic memory M_d

Output: AS_{seq}

Initialize S, S_c, T_d, and U
for each slide S_n in S **do**
  Parse slide contents and identify regions R in S_n
  Analyze script for current slide S_n
  for each region R_n in R **do**
    $L_n \longleftarrow$ assign segment label L to region R_n
    $S_{cn} \longleftarrow$ add appropriate speech segment
    $segment_n \longleftarrow$ write segment data to M_d
  end for
  for each $segment_n$ in slide S_n **do**
    Analyze $segment_n$
    $a_n \longleftarrow$ assign suitable action (RN or HW)
    $r_n \longleftarrow$ give rationale for action
    $\mathcal{H} \longleftarrow$ write salience heuristic data to M_d
  end for
  $\mathcal{T} \longleftarrow$ save segmentation and analysis data to M_L
end for
TasaAgent utilizes $\mathcal{T}$ to generate AS_{seq}
return AS_{seq}

4 Experiments

We conducted extensive quantitative and qualitative evaluations of LectūraAgents through diverse experiments, assessing the framework's performance on the following pedagogical metrics: lecture content quality, teaching quality, assessment, and personalization.

Our main goal is to provide answers to two fundamental research questions:

1. **RQ1**: How does leveraging an adaptive hierarchical multi-agent architecture create high-quality personalized lecture contents that align with diverse learning profiles?
2. **RQ2**: How can an embodied tutor agent utilize generated materials to execute coherent, visual, and pedagogically informed teaching actions in a teaching environment (*e.g.*, lecture slides presentation)?

4.1 Experiment Setup

The experiments were designed to assess the framework from end-to-end, evaluating both personalized lecture generation and embodied teaching capabilities. We start by performing pedagogical evaluation on 280 personalized lectures generated using the framework under the seven frontier models reported in Table 4. For each model, we generate 40 lectures, with 10 lectures for each academic level, using the same prompts, learner profiles, and text-to-speech model (Kokoro TTS [62]) to ensure a fair comparison. Details on these lectures can be found in Appendix A.2.2. We worked with five expert educators, including subject teachers and university instructors with experience in curriculum design and instructional assessment, to define pedagogical rubrics grounded in recognized instructional quality standards [66], as summarized in Table 3. Additional details on the recruitment of these experts can be found in Appendix A.2.4. We then adopted the evaluation method in TutorBench [67], with scoring primarily done by the expert educators in order to avoid induced bias from an LLM judge. Thus, for a j-th lecture, the framework's overall performance score for each session under a given model or baseline framework, is computed as the weighted average of all passed rubric criteria AAR^j_w, given by:

$$AAR^j_w = \frac{\sum_{i=1}^{N_j} w^j_i \cdot \mathbf{1}_{r^j_i}}{\sum_{i=1}^{N_j} w^j_i \cdot \mathbf{1}_{w^j_i > 0}} \tag{4}$$

where N_j is the number of rubric criteria for the j-th lecture, $w^j_i \in$ {-5, -3, -1, 0, +1, +3, +5}, is the weight assigned to the i-th criterion, and $r^j_i \in \{0,1\}$ indicates whether criterion i is satisfied. When a criterion is satisfied $r^j_i = 1$, it contributes a positive reward of +5, +3, or +1, corresponding to it being a highly desirable, desirable and important, or nice-to-have behavior, respectively. When a criterion is not satisfied $r^j_i = 0$, it is explicitly treated as a failure state and contributes a non-positive score, spanning a 0, -1, -3, and -5 range: 0 denotes the lowest-severity failure (no credit), -1 is used for a minor failure, -3 for a moderate failure, and -5 represents a critical failure (highly undesirable behavior).

4.1.1 Lecture Generation Evaluation

Here, we evaluate LectūraAgents as a personalized lecture content generator. For each model, we generated 40 personalized lectures covering math, science, engineering, art, and history, with 10 lectures each for high school, undergraduate, master's, and PhD learning profiles. Topics were randomly selected with emphasis on science subjects. Each lecture targeted one individual learner profile, covering learners aged 13–35, with profiles varying by academic level, prior knowledge, learning goals, learning style, and expected difficulty. The resulting output after generation contains the following lecture artifacts: a detailed lecture plan, a research report, syllabus, learner profile, 15 slides with images, per-slide scripts, lecture speeches, personalized lecture notes and study guide, teaching actions, teaching action–speech alignment, and assessments.

Table 3: Evaluation metrics and their respective rubrics

Lecture Generation	
Evaluation Metric	**Rubrics**
Lecture Content Quality (LCQ)	*Accuracy, Clarity, Coherence, Cognitive Load, Syllabus Coverage, Instruction-following*
Personalization Quality (PQ)	*Adaptive Emphasis, Preference Alignment, Engagement, Motivation, Tone/Style*
Assessment Quality (AQ)	*Concept Coverage, Cognitive Appropriateness, Answer Validity; Rationale*
Lecture Delivery	
Teaching Action Quality (TAQ)	*Temporal Alignment, Accurate Handwriting Action, Accurate Rough Notation Action, Spatial Accuracy, Active Learning, Embodied Teaching*

Evaluation Metrics. Using expert-defined rubrics detailed in Table 3, we assess the framework's personalized lecture content generation capability across three main evaluation metrics: Lecture Content Quality (LCQ), Personalization Quality (PQ), and Assessment Quality (AQ). LCQ measures accuracy, clarity, coherence, cognitive load, and instruction-following rubric dimensions. PQ evaluates adaptation to a learner profile (adaptive emphasis) and learning preferences (preference alignment), engagement, motivation, and instructor's tone or style. AQ measures concept coverage, cognitive appropriateness, answer accuracies, and rationale quality. Each lecture's metric score is computed using the weighted average of all passed rubrics and then averaged across all 40 lectures generated under each model.

4.1.2 Lecture Delivery Evaluation

Next, we evaluate the embodied and multimodal teaching capability of the framework. For each generated lecture, the *ProfessorAgent* is tasked with teaching all 15 slides using lecture artifacts created in the lecture generation session. This stage evaluates the agent's teaching action quality, independent of content generation, allowing us to assess multimodal alignment and embodied instructional delivery capabilities specifically.

Evaluation Metrics. Lecture delivery is evaluated using the Teaching Action Quality (TAQ) metric, which has six rubric dimensions (detailed in Table 3). These include temporal and spatial alignment of teaching actions, accurate handwriting and rough notation actions, active learning, and overall embodied teaching experience. TAQ assesses how well each model exploits the frameworks architecture to deliver accurate, coherent, and pedagogically informed teaching action sequences. For each slide, script, and teaching action sequence, an expert educator judges whether each rubric criterion is satisfied, and the overall average TAQ score is computed using Equation 4.

Table 4: (RQ 1) Evaluation of LectūraAgents across pedagogical metrics under frontier models

Rank	Model	LCQ (%)	PQ (%)	AQ (%)	TAQ (%)	AAR (%)
1	Gemini 3 Pro	80.2	83.3	81.6	76.5	**80.4**
2	GPT-5.1	76.1	80.5	82.3	76.2	**78.8**
3	Claude 4.5 Sonnet	72.4	78.6	76.2	80.4	**76.9**
4	Gemini 2.5 Pro	70.5	75.2	80.1	72.3	**74.5**
5	DeepSeek V3.2	68.9	73.1	75.2	77.8	**73.5**
6	GPT-4o	67.5	71.4	72.8	73.2	**71.2**
7	Qwen 3 Omni	65.4	70.3	56.5	64.3	**64.1**

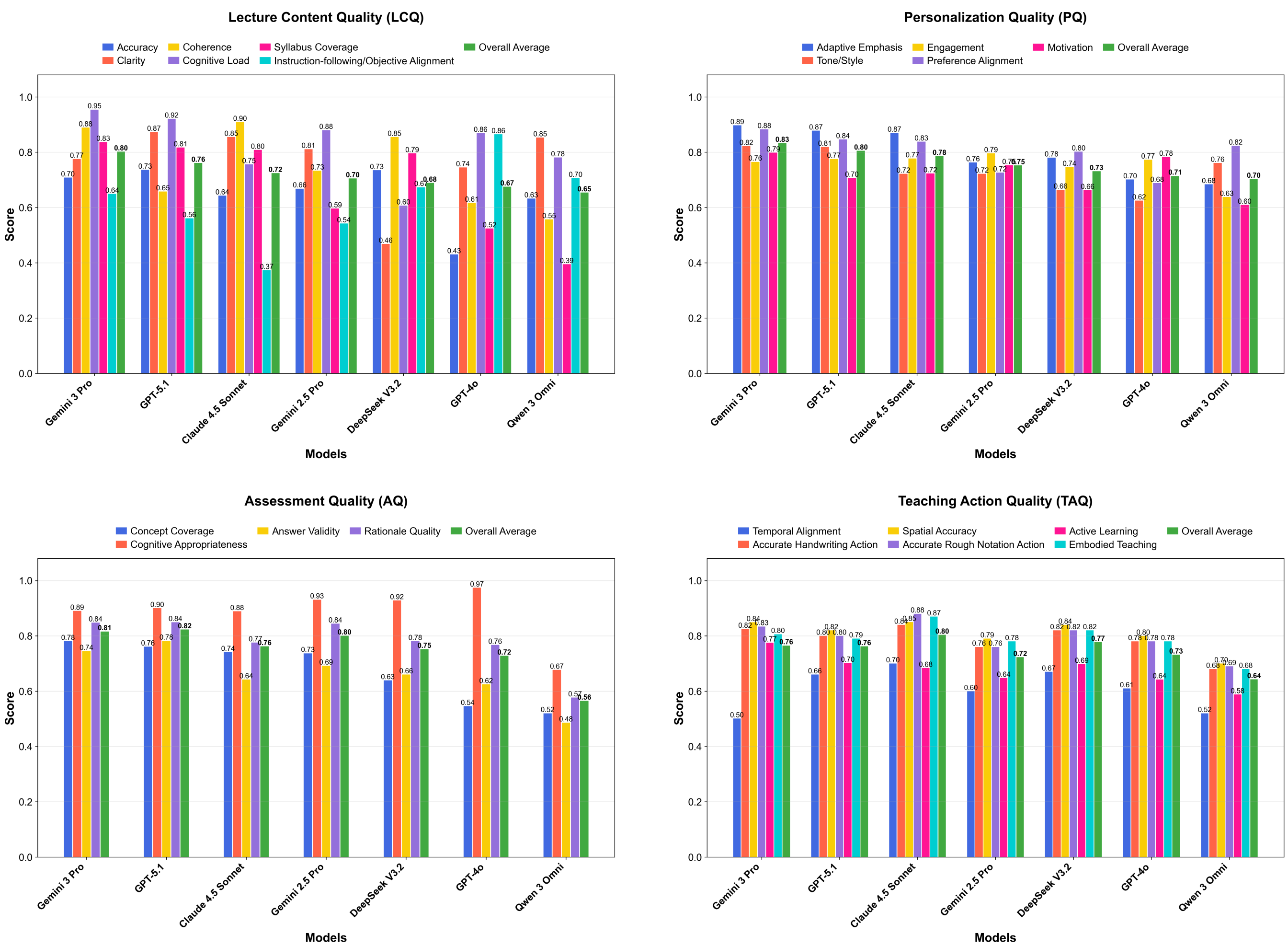

Figure 9: (RQ1 and RQ2) Results across rubric dimensions for each evaluation metric under each frontier model.

Results. TAQ results indicate that LectūraAgents enables generally accurate and coherent teaching action sequences across models. As shown in Figure 9, models perform strongly on spatially grounded criteria, particularly spatial accuracy, handwriting actions, rough notation actions, and embodied teaching. This suggests that the framework can reliably convert generated lecture materials into visible instructional actions. Figure 10 further shows that teaching-action-related scores are distributed across multiple lecture artifacts, indicating that embodied delivery is maintained across the broader lecture package rather than appearing only in isolated outputs. A key factor behind this stability is the TASA module, which provides the *ProfessorAgent* with a structured view of slide regions and aligns teaching actions with corresponding speech segments. While temporal alignment remains comparatively more

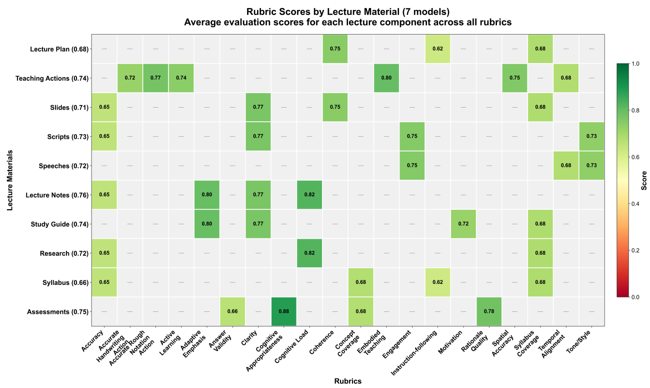

Figure 10: (RQ2) Average distribution of Personalization Quality and Teaching Action Quality across diverse learning profiles at various academic levels.

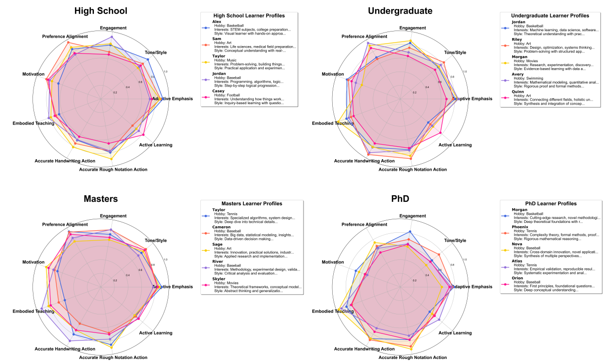

Figure 11: (RQ2) Overall average distribution of Lecture Content Quality scores across generated Lecture Materials from all models.

variable due to the difficulty of fine-grained action–speech synchronization, Figure 11 shows that TAQ and personalization-related performance remain broadly stable across all learner profiles. This suggests that the embodied teaching mechanism generalizes across academic levels, while timing-sensitive action selection remains an area for addiitonal improvement.

4.1.3 Comparative Evaluation with Related Frameworks

We further assess LectūraAgents against existing frameworks in this domain. Due to varying capabilities between baselines, we only compare performances on shared capabilities to ensure fairness. We identify two closely related open-source frameworks and one learning system with publicly available lecture data: Instructional Agents [34], GenMentor [36], and Google's Learn Your Way system [3]. Our comparative evaluation assesses each framework or system based on lecture content quality (LCQ), assessment quality (AQ), and personalization (PQ) evaluation metrics, using the same evaluation method described in Section 4.1. For InstructionalAgents and GenMentor, we generated 20 lectures using their publicly released implementations. For Learn Your Way, we used the publicly available lectures provided on its website. Additional details about the lecture set and selection process are provided in Appendix B. We then generated the same lectures with LectūraAgents using identical topics, prompts, and learner profiles, and evaluated all outputs using the methodology described in Section 4.1.

Results. As shown in Table 5, LectūraAgents obtains higher scores than the baseline systems across LCQ, PQ, and AQ. The most notable difference is observed in personalization quality, indicating that the framework is better able to adapt generated materials to learner profiles. Its performance in lecture content and assessment quality further suggests that the framework supports not only learner-specific adaptation, but also coherent instructional organization and alignment between lecture materials and assessment tasks.

4.1.4 Efficacy Study with Students

The preceding evaluations assessed the pedagogical capabilities of the framework across multiple topics, models, and personalization settings. However, the impact of the framework is better examined when these capabilities are tested on real learners. Therefore, we conducted a small-scale efficacy study with real students to measure the holistic pedagogical value of LectūraAgents in terms of learning support and learner experience. To provide a broader comparison, we included both Learn Your Way, representing a modern AI-assisted learning system, and Adobe Acrobat Reader v23.008.20555, representing a widely used traditional digital study

Table 5: Performance comparison of LectūraAgents with existing related frameworks

	N (number of lectures) = 20			
Framework / System	**LCQ (%)**	**PQ (%)**	**AQ (%)**	**Overall (%)**
Instructional Agents [34]	52.1	53.2	51.4	52.2
GenMentor [36]	50.8	64.6	46.6	54.0
Learn Your Way [3]	58.9	60.1	62.5	60.5
LectūraAgents	**70.3**	**73.5**	**71.2**	**71.6**

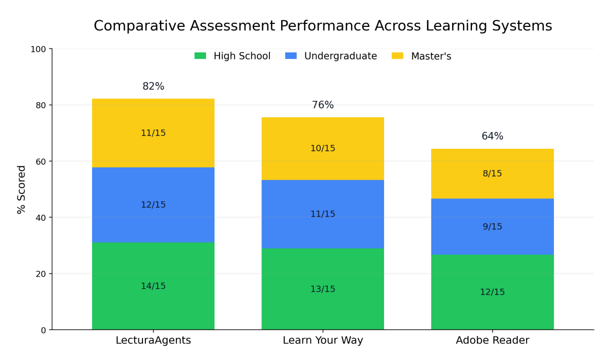

Figure 12: Average scores from immediate assessment on topics learned using LectūraAgents, Learn Your Way, and Adobe reader.

Table 6: Student responses to a survey given after assessment

To what extent do you agree or disagree with the following statements? % somewhat agree or strongly agree	**LectūraAgents N = 15**	**Learn Your Way N = 15**	**Adobe Reader N=15**
I felt adequately prepared to complete the assessment after using today's educational tool.	95%	80%	72%
I felt like today's educational tool helped me gain a good understanding of the topic.	100%	92%	65%
I would like to use today's educational tool to support my learning needs in the future.	87%	73%	63%
The educational tool I used today would make me more effective at learning compared to other educational tools I currently use at home or in school.	84%	67%	44%

reading software without generative AI capabilities. The study involved 45 students divided equally across the three learning systems, with 15 participants per system. Each group comprised five students from each educational level—high school, undergraduate, and master's—with ages ranging between 15 to 25 years. Students were recruited through a short pre-study topic-familiarity screening and provided informed consent prior to participation.

Result. Figure 12 compares students' post-learning assessment performance across learning systems. The results show that LectūraAgents achieved the strongest performance across all learner groups, followed by Learn Your Way and Adobe Reader. Although the improvement is modest, its consistency suggests that the framework's personalized and embodied teaching capabilities supported better short-term comprehension and content recall, rather than merely improving students' subjective learning experience. Consistent with this pattern, Table 6 shows that students using LectūraAgents reported stronger perceived content understanding, assessment readiness, future learning support, and overall learning experience than those using Learn Your Way or Adobe Reader.

5 Limitations and Future Work

We acknowledge several limitations that may inform future work. First, while LectūraAgents performs well on lecture content generation and embodied delivery, the current teaching action–speech alignment module relies heavily on offline heuristics with a limited set of supported teaching actions. This may constrain the richness of embodied instruction and robustness across diverse slide layouts. Second, the multi-agent orchestration can introduce latency and compute overhead. Finally, the framework can sometimes inherit common LLM failure modes such as factual errors, inconsistent reasoning, and tool or prompt-sensitivity. Future work will (1) expand the teaching action taxonomy and improve action fidelity; (2) transition from heuristic action–speech alignment to learned policies (*e.g.*, training policies in a presentation slide environment with preference optimization or reinforcement learning); (3) strengthen grounding to reduce hallucinations; and (4) optimize orchestration for efficiency while preserving pedagogical coherence and controlling compute costs.

6 Conclusion

In this paper we introduced LectūraAgents, a hierarchical multi-agent framework for end-to-end adaptive, personalized AI-assisted learning experiences. The framework addresses two major issues in personalized AI-assisted learning: (1) How can AI adaptively personalize instructional contents to best meet the needs of diverse learners? (2) How can such instructional contents be delivered in embodied and pedagogically meaningful ways to ensure better learning outcomes? In order to effectively address these issues, LectūraAgents is first modelled on a professor-student relationship framing, wherein a *ProfessorAgent* leads a collaborative class of specialized subordinate agents through research, planning, evaluation, and embodied delivery of instructional contents that adapt to diverse students. The framework's personalized and embodied capabilities (*e.g.*, TASA algorithm) offer students enhanced learning and study experiences. We evaluated LectūraAgents through two main experiments: a pedagogical evaluation under frontier models across high school, undergraduate, and graduate-level topics, and an efficacy study with real students. Experimental results show substantial improvements over baseline frameworks in lecture content quality, personalization, assessment quality, and embodied teaching performance. In addition, these findings are validated by results from our efficacy study with students, which provide preliminary evidence that the framework can improve learning outcomes while enhancing learner experience. In conclusion, we position LectūraAgents offers as a pedagogically grounded framework for personalized AI-assisted learning at scale.

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Appendix A

A.1 LectūraAgents: Detailed Architecture

A.1.1 Core Modules and Components

The framework is organized into four core modules, each serving a distinct purpose in the lecture generation and lecture delivery stages. These modules provide the infrastructure for agent coordination, LLM integration, teaching action alignment, memory management, and content rendering. The modular design enables easy extension and maintenance of individual components.

Table A1: LectūraAgents' Core Modules and Components

Module	Location	Function	Key Classes
Agents	Lectura/LecturaAgents/module/agents	The Agents module implements the core agent architecture with base interfaces, role definitions (Coordinator, Executor, Validator), and state management. This module provides the hierarchical three-tier agent system with collaboration mechanisms (sequential and parallel) and orchestration through SwarmOfRanks. It handles agent lifecycle, task execution, validation, and inter-agent communication.	Agent (base class), ProfessorAgent, LecturePlanner, ResearchAgent, SlideAgent, ScriptAgent, SpeechAgent, TasaAgent
LLMs	Lectura/LecturaAgents/module/llms	Provides unified abstraction layer for multiple LLM providers (OpenAI, Google, Anthropic, DeepSeek, Qwen, Local) enabling seamless model switching. Handles authentication, API communication, response formatting, function calling, and streaming. It abstracts provider-specific differences to provide consistent interface for all agents.	LLMProvider (base class), OpenAIProvider, GoogleAIProvider, AnthropicProvider, DeepSeekProvider, QwenProvider, LocalLLMProvider
TASA	Lectura/LecturaAgents/tasa	Implements Teaching Action Salience Analysis (TASA) for generating and aligning synchronized teaching actions (rough notation, handwriting) with speech. This module processes speech scripts to embed action markers, extracts word-level timestamps from audio using Whisper ASR [63], and creates temporal alignment between visual actions and spoken content.	TASA
Adaptive Memory	Lectura/LecturaAgents/memory	Implements a three-layer adaptive memory system: short-term memory for session context, long-term memory for persistent learner data, and dynamic memory for adaptive learning patterns. This module provides a unified AdaptiveMemory interface that enables agents to access learner context, preferences, and learning history for personalization.	ShortTermMemory, LongTermMemory, DynamicMemory, AdaptiveMemory

A.1.2 Agent Hierarchy and Roles

Agents are organized by rank and responsibility. Rank 1 agents (ProfessorAgent) serve as coordinators and validators at the highest level, Rank 2 agents (LecturePlanner, ResearchAgent) coordinate execution and validate outputs, while Rank 3 agents (SlideAgent, ScriptAgent, SpeechAgent, TasaAgent) execute specific tasks. Each agent has clearly defined responsibilities and access to appropriate tools and actions for their role.

Table A2: Agent Hierarchy and Roles

Rank	Agent	Role	Responsibilities	Tools / Actions
1	ProfessorAgent	Coordinator and Tutor	• Initiates lecture sessions • Reviews and approves plans • Validates final artifacts • Reviews final lecture artifacts • Delivers embodied lectures	research() create_syllabus() review_plan() instantiate_groupchat() create_lecture_notes() create_study_guide() create_assessments() create_personalization() review_artifacts() embodied_teaching()
2	Lecture Planner	Validator	• Creates lecture plans. • Manages and validates tasks done by subordinate executor agents. • Assembles generated lecture artifacts and submits to ProfessorAgent for final review.	research() create_plan() validate_task() assemble_artifacts()
3	Executor Agents	Executors	**ResearchAgent:** Conducts multi-turn web searches on lecture topic, writes a detailed research report and submits for review by LecturePlanner.	web_search()
			SlideAgent: Generates personalized slide contents; Designs and build slides with structured content blocks based on learner's preferences.	slide_builder() research() file_parser()
			ScriptAgent: Creates engaging, personalized narration scripts that aligns with both slide contents and learner's preferences.	analyze_slide() write_script()
			SpeechAgent: Synthesizes and generates speech audio from scripts based on learner's preferred instructor voice. Uses TTS/ASR tool to create word-level timestamps .	Whisper [63], Kokoro TTS [62] create_timestamps()
			TasaAgent: Uses tools in TASA module to segment and annotate slide contents with heuristic based context for prospective action-speech sequences. It then processes speech timestamps and slide contents into synchronized embodied teaching action sequences with embeded action markers (highlight, underline, handwriting, etc.).	TASA Module temporal_segmentation() heuristic_analysis()

A.1.3 Agent States and Lifecycle

Agents transition through a well-defined state machine during task execution. The lifecycle begins with the IDLE state, progresses through acknowledgment and execution phases, and concludes with completion, failure, or revision states. This state management ensures proper task tracking, error handling, and enables agents to revise their work based on feedback from higher-ranking agents.

Table A3: LectūraAgents' States and Lifecycles

State	Description	Transition
IDLE	Agent is waiting for a task.	ACKNOWLEDGED

State	Description	Transition
ACKNOWLEDGED	Agent has received and acknowledged given.	EXECUTING
EXECUTING	Agent is actively working on assigned task.	COMPLETED, FAILED or REVISAL
COMPLETED	Agent has completed task successfully.	IDLE (for next task)
FAILED	Task execution was unsuccessful.	REVISAL
REVISAL	Agent is revising work based on feedback from self-reflection or review.	EXECUTING

A.1.4 Multi-agent Collaboration

Agents within the same rank can collaborate using two primary mechanisms: sequential collaboration for dependent tasks and parallel collaboration for independent tasks. The SwarmOfRanks mechanism enables hierarchical coordination across multiple ranks, allowing complex workflows where agents at different levels coordinate their activities. These collaboration patterns are essential for orchestrating the multi-stage lecture generation process.

Table A4: Collaboration Mechanisms

Type	Description	Use Case
Sequential Colab	Agents complete tasks one after another, sharing responses.	When tasks depend on previous outputs.
Parallel Colab	Agents complete tasks simultaneously, while sharing responses.	When tasks are independent.
Swarm of Ranks	Hierarchical coordination across ranks	Multi-rank workflows

A.1.5 Tools and Capabilities

The framework provides a comprehensive set of tools that agents use to accomplish their tasks. These tools range from web search and file parsing to text-to-speech synthesis and code execution. Each tool is designed to be modular and reusable, with clear interfaces that agents can invoke during their execution. The tools abstract away complex operations like API interactions, file processing, and multimedia generation.

Table A5: Tools and Capabilities

Tool	Purpose	Usage	Dependencies
Web Search	Multi-turn web research using SerpAPI.	Used by *ResearchAgent, ProfessorAgent, LecturePlanner* and *SlideAgent*	SerpAPI
Slide World	Dynamic slide environment with canvas for teaching sessions.	Used by *ProfessorAgent* for embodied lecture delivery.	HTML/CSS/JS/Python
Slide Builder	Custom slide design tool.	Used by *SlideAgent* for building and rendering slides.	HTML/CSS/JS/Python
File Parser	Parses PDF, TXT, MD files.	Used by *ProfessorAgent* and *SlideAgent* to extract content from additional materials.	PyPDF2, python-docx
Command line	For command execution to create lecture artifacts.	Used by all agents to read/write/edit/save/delete files.	Bash/Zsh
TASA Segmentor / Aligner	Segments, annotates and aligns slide contents with speech timestamps for synchronized	Used by *ProfessorAgent* and *TasaAgent*	TASA Module
Research	A unified research tool that makes use of web search plus an LLM to perform deep research on topics.	Used by *ResearchAgent, ProfessorAgent, LecturePlanner* and *SlideAgent*	SerpAPI + Underlying LLM
Whisper [63]	Extracts word-level timestamps from audio.	Used by *TasaAgent* for action alignment.	Whisper ASR model

Tool	Purpose	Usage	Dependencies
Kokoro TTS [62]	Generate speeches from scripts with desired instructor voice.	Used by *SpeechAgent* for speech synthesis.	Kokoro TTS

A.1.6 Adaptive Memory

LectūraAgents utilizes a three-layer memory architecture to support adaptive and personalized learning experiences. Short-term memory captures recent interactions within a session, long-term memory stores persistent learner-specific data across sessions, and dynamic memory adapts to learning patterns and preferences. The adaptive memory module provides a unified interface that combines all three memory types, enabling agents to access relevant context efficiently.

Table A6: Memory Types and Functionalities

Memory Type	Function	Storage	Update Frequency
Short-term Memory	Handles recent interactions and context.	In-memory (session-based)	Per interaction
Long-term Memory	Manages persistent learner-specific data.	File-based (JSON)	Per session
Dynamic Memory	Adaptive learning patterns and preferences.	In-memory + file-based	Continuously updated

A.1.7 LLMs

We ensure the framework supports multiple frontier models from leading LLM providers through a unified API, allowing seamless switching between different models based on task requirements, cost considerations, and performance needs. Each provider implementation handles authentication, API communication, and response formatting, while the unified interface ensures that agents can work with any supported model without code changes. This design enables flexibility in choosing the most appropriate model for each task.

Table A7: Supported LLM Providers and Models

LLM Provider	Supported Models
OpenAI	GPT-5.1, GPT-4o, o3-pro
Google AI	Gemini 3 Pro, Gemini 2.5 Pro, Gemini Flash 2.5 Lite
Anthropic	Claude 4.5 Sonnet, Claude 4.1 Sonnet
DeepSeek	DeepSeek V3.2, DeepSeek-R1

A.1.8 Slide Content Block Types

To ensure accurate alignment and rubust slide contents, we ensure each slide can support multiple content block types that enable rich, structured presentation of information. Each block type is designed for specific pedagogical purposes, from definitions and equations for core concepts to examples, steps, and questions for engagement. The framework automatically renders these blocks with appropriate styling and formatting, ensuring consistent visual presentation across all slides.

Table A8: Various Types of Slide Content Blocks

Block Type	Description	Rendering	Usage
Bullets	Brief, concise key points about concepts and topics.	HTML list elements (, , etc.)	Holds main contents for topic
Definition	Key term definitions.	HTML styled definition div	Core concepts
Example	Concrete examples	HTML highlighted example div	Examples
Equation	Mathematical equations	LaTeX rendering in a div	Formulas, proofs
Question	Interactive questions	HTML Question box div	Engagement
Link	External references	hyperlink / link element	Resources
Table	Structured data	HTML table element	Comparisons, data
Video	YouTube video embeds	HTML iframe element	Educational short videos
Image	Illustrative and educative images with captions	HTML image element	Illustration
Steps	Step-by-step procedures	HTML numbered list	Algorithms, processes, etc.

A.2 More on Evaluation Methodology

A.2.1 Overview

Our evaluation adopts a rubric-based methodology for both pedagogical and comparative assessment, with generated learning and teaching artifacts scored and validated by expert educators. The evaluation examines two core capabilities of the framework: its ability to generate high-quality personalized lecture content for diverse learner profiles, and its ability to utilize these generated materials during embodied teaching. Specifically, we evaluate LectūraAgents using four main metrics: Lecture Content Quality (LCQ), Personalization Quality (PQ), Assessment Quality (AQ), and Teaching Action Quality (TAQ). These metrics are applied across three evaluation settings: (1) Pedagogical Evaluation under Frontier Models, which assesses personalized lecture generation and embodied lecture delivery across different frontier models; (2) Comparative Evaluation with Related Frameworks, which compares LectūraAgents with existing educational agent or personalized learning frameworks, including InstructionalAgents, LearnYourWay, and GenMentor; and (3) Efficacy Study with Students, which examines the framework's practical learning support and learner experience using real student participants.

A.2.2 LectūraAgents' Pedagogical Evaluation Under Frontier Models

During this evaluation, we generated 40 lectures per model across seven models, resulting in 280 lectures in total. For each model, the lecture set included 10 lectures per academic level, with 20 learner profiles in total (five profiles per level). The topics covered science, engineering, history, art, and business. Details on these lectures can be found in the released dataset, available at HuggingFace[1]. The generated lecture artifacts were assessed across four evaluation metrics: Lecture Content Quality (LCQ), Personalization Quality (PQ), Assessment Quality (AQ), and Teaching Action Quality (TAQ). The evaluation followed a two-stage procedure. In Stage 1, an LLM analyst provided structured rubric-based analysis for each lecture, identifying evidence relevant to the instructional criteria under each metric, as detailed in Table A9 and Table A10. In Stage 2, expert educators reviewed the LLM-generated analysis, validated the evidence, assigned the final rubric scores, and made corrections where necessary. The verified scores were then aggregated to compute metric-level scores, overall averages, visualizations, and comparative insights into model performance across academic levels and evaluation dimensions.

Table A9: Stages in Pedagogical Evaluations

Stage	Task	Command	Output
Stage 1	An LLM (GPT 5.2) gives detail analysis of generated lecture contents per academic level based on rubrics or criteria in the evaluation metrics.	python3 evaluate.py \ --model model_name \ --lecture lecture_name \ --level level_name \ --llm analysis_model	(JSON) Detailed analysis for each generated lecture at each academic level under a model.
Stage 2	An expert educator validates, scores and aggregate results for respective rubrics.	python3 evaluate.py \ --aggregate \ --lecture lecture_name \ --level level_name	(JSON, Charts) Comprehensive scores and results.

Table A10: Details on Evaluation Metrics, Rubrics, Descriptions and Their Input Files

Lecture Generation Evaluation			
Evaluation Metric	**Rubrics / Criteria**	**Description**	**Input Files**
Lecture Content Quality (LCQ)	*Accuracy*	Verifies factual correctness across all generated materials.	All generated files
	Clarity	Assesses clarity of explanation across teaching materials.	lecture_plan.json, learner_profile.txt, syllabus.json, scripts.json, slides_content.json, slides/*.html, lecture_notes_/*.md, quiz.json, and exam.json
	Coherence	Evaluates logical flow across all materials.	All generated files
	Cognitive Load	Assesses lecture contents alignment with learner's background or level.	learner_profile.txt, syllabus.json, scripts.json, slides_content.json, slides/*.html, lecture_notes_/*.md, quiz.json, and exam.json

[1]HuggingFace dataset: https://huggingface.co/datasets/Jaward/lectura-agents-data

Evaluation Metric	Rubrics / Criteria	Description	Input Files
	Syllabus Coverage	Verifies topic coverage.	syllabus.json, scripts.json, slides_content.json, slides/*.html, lecture_notes_/*.md, quiz.json, exam.json, and study_guide.md
	Instruction-following	Checks framework's adherence to instructions, tasks or prompts.	All generated files
Personalization Quality (PQ)	*Adaptive Emphasis*	Assesses the framework's ability to adapt instructions to the learner's learning preferences or profile through.	learner_profile.txt, scripts.json, slides_content.json, slides/*.html, lecture_notes_/*.md quiz.json, exam.json, and study_guide.md
	Preference Alignment	Checks content alignment with learning preferences.	teaching_actions.json, scripts.json, slides_content.json, slides/*.html, lecture_notes_/*.md, quiz.json, exam.json, and study_guide.md
	Engagement	Evaluates framework's capability to consistently engage the learner.	teaching_actions.json, scripts.json, slides_content.json, slides/*.html, lecture_notes_/*.md, quiz.json, exam.json, and study_guide.md
	Motivation	Evaluate motivational elements across learning materials.	teaching_actions.json, scripts.json, slides_content.json, slides/*.html, lecture_notes_/*.md, quiz.json exam.json, and study_guide.md
	Tone/Style	Evaluate language appropriateness	scripts.json, slides_content.json, lecture_notes_/*.md, study_guide.md, and learner_profile.txt
Assessment Quality (AQ)	*Concept Coverage*	Verifies whether assessments covered all topics in the syllabus.	quiz.json, exam.json, syllabus.json, slides_content.json
	Cognitive Appropriateness	Evaluates assessment difficulty and its alignment with the learner's profile.	learner_profile.txt, quiz.json, exam.json, syllabus.json, slides_content.json
	Answer Validity	Checks accuracy of solutions to assessments.	quiz.json, exam.json, syllabus.json, slides_content.json
	Rationale	Evaluates the quality of explanation in solutions.	quiz_solutions.json, exam_solutions.json
Lecture Delivery Evaluation			
Evaluation Metric	**Rubrics / Criteria**	**Description**	**Input Files**
Teaching Action Quality (TAQ)	*Temporal Alignment*	Validates action-speech alignments.	action_speech_alignment.json, scripts.json, speech_timestamps.json
	Accurate Handwriting Action	Checks accuracy of handwriting actions, *i.e.*, whether words or phrases are written clearly and correctly at the right time frame.	slides/*.html (after applied actions), action_speech_alignment.json
	Accurate Rough Notation	Checks accuracy of rough notation actions, *i.e.*, whether notations like highlight, underline, and circle actions are applied correctly in the right region and at the right time frame.	slides/*.html (after applied actions, action_speech_alignment.json
	Spatial Accuracy	Verifies annotation precision.	slides/*.html (after applied actions), action_speech_alignment.json
	Active Learning	Assesses the effect of teaching actions on the learner's engagement or focus during teaching.	slides/*.html, quiz.json, exam.json, action_speech_alignment.json

Evaluation Metric	Rubrics / Criteria	Description	Input Files
	Embodied Teaching	Evaluates overall embodied teaching experience.	tasa_analysis.json, teaching_actions.json, slides/*.html (after applied actions), action_speech_alignment.json, scripts.json, speech_timestamps.json

A.2.3 Rating

Each rubric or criteria is evaluated as a boolean (satisfied or not), and these boolean scores are weighted and averaged to produce Average Achieved Ratings (AARs) at the metric and overall levels. Thus, for the j-th lecture, the overall performance score for under a given model, is computed as the weighted average of all passed rubric criteria AAR_w^j, given by:

$$AAR_w^j = \frac{\sum_{i=1}^{N_j} w_i^j \cdot \mathbf{1}_{r_i^j}}{\sum_{i=1}^{N_j} w_i^j \cdot \mathbf{1}_{w_i^j > 0}}$$

where N_j is the number of rubric criteria for the j-th lecture, $w_i^j \in$ {-5, -3, -1, 0, +1, +3, +5}, is the weight assigned to the i-th criterion and $r_i^j \in$ {0,1}indicates whether criterion i is satisfied. When a criterion is satisfied $r_i^j = 1$, it contributes a positive reward of +5, +3 or +1, corresponding to a highly desirable, a desirable and important, or a nice-to-have behaviour, respectively. When a criterion is not satisfied $r_i^j = 0$, it is explicitly treated as a failure state and contributes a non-positive score, spanning 0, -1, -3, -5: 0 denotes the lowest-severity failure (no credit), -1 a minor failure, -3 a moderate failure, and -5 a critical failure (highly undesirable behaviour).

A.2.4 Expert Recruitment and Evaluation Procedure

Five expert educators were recruited through purposive sampling based on their experience in teaching, curriculum development, and educational assessment. The panel consisted of secondary-school teachers and university instructors from STEM, social science, and humanities disciplines, each with at least five years of teaching experience. Prior to the evaluation, the experts participated in an online workshop, during which the evaluation dimensions, criteria, and weighting scheme were reviewed and refined to ensure pedagogical relevance and consistency across educational levels and subject domains. During the evaluation, experts were assigned respective lecture samples according to their areas of expertise; they reviewed the generated lecture artifacts and assigned final scores based on the agreed-upon rubrics.

A.2.5 Comparative Evaluation of LectūraAgents with Related Frameworks

Comparative analysis was done against two multi-agent frameworks (Instructional Agents and GenMentor) and one system (Google's Learn Your Way). For the frameworks, we generated 20 lectures (5 for each level spanning 10 profiles) using their released code and then generated the same lectures with LectūraAgents and compared performances. Table A11 summarizes generated lecture topics and profiles per framework or system. For Google's Learn Your Way system, given that no source code was released we instead utilized their already generated sample lectures openly available on their website. We then generated these lectures with LectūraAgents and compared performances as well. Our comparative evaluation assesses each framework or system based on lecture content quality (LCQ), assessment quality (AQ) and personalization (PQ) evaluation metrics using the same evaluation method described in Appendix A.2.3 and Appendix A.2.4.

Table A11: Generated Lectures for Comparative Analysis

Framework / System	Lecture and Learner Profile Details
Instructional Agents and GenMentor	Lecture Title: *Newton's Laws of Motion* Learner Profile: *8th-grade high schooler interested in STEM, enjoys basketball, and prefers visual, hands-on learning through diagrams, examples, and practical activities.*
	Lecture Title: *Photosynthesis and Cellular Respiration* Learner Profile: *9th-grade high schooler interested in creative writing and music, enjoys sketching, and learns biology best through story-like explanations, visuals, and everyday analogies.*
	Lecture Title: *Quadratic Equations and Functions* Learner Profile: *10th-grade high schooler preparing for advanced mathematics, enjoys chess, and prefers worked examples, graph-based explanations, and short practice problems.*
	Lecture Title: *The Solar System and Planetary Motion* Learner Profile: *11th-grade high schooler interested in astronomy and planetary systems, enjoys tennis, and prefers simulations, diagrams, and applied problem solving.*
	Lecture Title: *World War II: Causes and Consequences* Learner Profile: *12th-grade high schooler interested in modern history and global conflict, enjoys soccer, and prefers timeline-based explanations with cause-and-effect reasoning.*

Framework / System	**Lecture and Learner Profile Details**
	Lecture Title: *Intro to Large Language Models* Learner Profile: *Undergraduate computer science student interested in artificial intelligence and language technologies, enjoys basketball, and prefers intuitive explanations followed by coding examples.*
	Lecture Title: *Machine Learning: Supervised vs Unsupervised* Learner Profile: *Undergraduate data science student interested in machine learning methods and data patterns, enjoys hiking, and prefers visual comparisons using real datasets.*
	Lecture Title: *Molecular Biology: Gene Expression* Learner Profile: *Undergraduate biology student interested in genetics and molecular regulation, enjoys swimming, and prefers process diagrams with concept checks.*
	Lecture Title: *Operating Systems: Process Scheduling* Learner Profile: *Undergraduate learner interested in environmental science and sustainability, enjoys photography, and learns systems concepts best through visual workflows, resource-allocation analogies, and practical examples.*
	Lecture Title: *Thermodynamics: Entropy and Free Energy* Learner Profile: *Undergraduate chemistry student interested in thermodynamics and energy transformations, enjoys cooking, and prefers equation walkthroughs connected to everyday examples.*
	Lecture Title: *Advanced Machine Learning: Deep Neural Networks* Learner Profile: *Master's-level engineering student interested in deep learning and neural architectures, enjoys tennis, and prefers model diagrams with optimization intuition.*
	Lecture Title: *Advanced Operating Systems* Learner Profile: *Master's-level systems student interested in distributed computing and resource management, enjoys cycling, and prefers architecture diagrams with performance trade-offs.*
	Lecture Title: *Computational Biology: Sequence Analysis* Learner Profile: *Master's-level computational biology student interested in genomics and sequence alignment, enjoys photography, and prefers algorithmic workflows with biological examples.*
	Lecture Title: *Cryptography and Network Security* Learner Profile: *Master's-level learner interested in ancient history and ethics, enjoys debate, and learns cryptography best through historical examples, trust scenarios, and clear protocol diagrams.*
	Lecture Title: *Distributed Systems Architecture* Learner Profile: *Master's-level computer science student interested in scalable systems and fault tolerance, enjoys tennis, and prefers system-design scenarios with failure cases..*
	Lecture Title: *Advanced Quantum Field Theory* Learner Profile: *PhD researcher interested in quantum fields and particle interactions, enjoys baseball, and prefers formal derivations supported by physical intuition.*
	Lecture Title: *Non-Equilibrium Statistical Mechanics* Learner Profile: *PhD researcher interested in statistical physics and complex systems, enjoys tennis, and prefers rigorous mathematical development with simulation examples.*
	Lecture Title: *Synthetic Biology: Circuit Design* Learner Profile: *PhD researcher interested in synthetic biology and programmable cellular circuits, enjoys running, and prefers circuit schematics with lab-oriented examples.*
	Lecture Title: *Topological Data Analysis in ML* Learner Profile: *PhD researcher interested in topology and machine learning geometry, enjoys rock climbing, and prefers visual abstractions grounded in data examples.*
Learn Your Way	Lecture Title: *Atoms and Molecules* Learner Profile: Middle schooler who likes reading.
	Lecture Title: *Carbon* Learner Profile: *Undergrad who likes painting.*
	Lecture Title: *Microeconomics and Macroeconomics* Learner Profile: *Undergrad who likes food.*
	Lecture Title: *Logical Statements* Learner Profile: *Undergrad who likes writing.*
	Lecture Title: *The Ancient Roman Economy* Learner Profile: *Undergraduate who likes plants..*

Framework / System	**Lecture and Learner Profile Details**
	Lecture Title: *The 'Long-Haired' Comets* Learner Profile: *Undergraduate who likes movies..*
	Lecture Title: *Early Human Evolution and Migration* Learner Profile: *Undergrad who like tennis..*
	Lecture Title: *Intro to Data Structures and Algorithms* Learner Profile: *High schooler who likes basketball.*
	Lecture Title: *Critical Reading and Evidence-Based Response* Learner Profile: *Middle schooler who likes soccer.*
	Lecture Title: *Disruptions in the Immune System* Learner Profile: *Middle schooler who likes food*
	Lecture Title: *Earth and Sky* Learner Profile: *Middle schooler who likes photography*
	Lecture Title: *Theories of Slef-development* Learner Profile: *Undergrad who likes cooking.*
	Lecture Title: *What is Learning* Learner Profile: *Undergrad who likes music.*
	Lecture Title: *"Reading" to Understand and respond* Learner Profile: *Middle schooler who likes music.*
	Lecture Title: *Micronomics and Macronomics* Learner Profile*: Undergrad who likes cooking.*
	Lecture Title: *An Overview of Economic Systems* Learner Profile: *High schooler who likes movies.*
	Lecture Title: *Early Human Evolution and Migration* Learner Profile: *Undergrad who likes tennis*

Appendix B

B.1 Code and Data

The data supporting this study is currently available on our huggingface repository at: https://huggingface.co/datasets/Jaward/lectura-agents-data. The code can be made available upon reasonable request from the corresponding author. Please follow the installation instructions below or in the readme file to get started.

B.1.1 Installation and Usage

1. Add all required api keys inside the .env file in the parent directory. You will need to provide two main api keys (1) for the LLM you want to use (OpenAI, Anthropic, Gemini and Deepseek); (2) A SerpApi key for research, while this is optional, it highly recommended to add one, as it helps reduce hallucination. Get key here: https://serpapi.com/manage-api-key

2. Cd into the parent directory and install all required packages using this command:

   pip3 install -r requirements.txt

3. If you wish to use the frontend for lecture generation, start the app with this command:

   python3 main.py

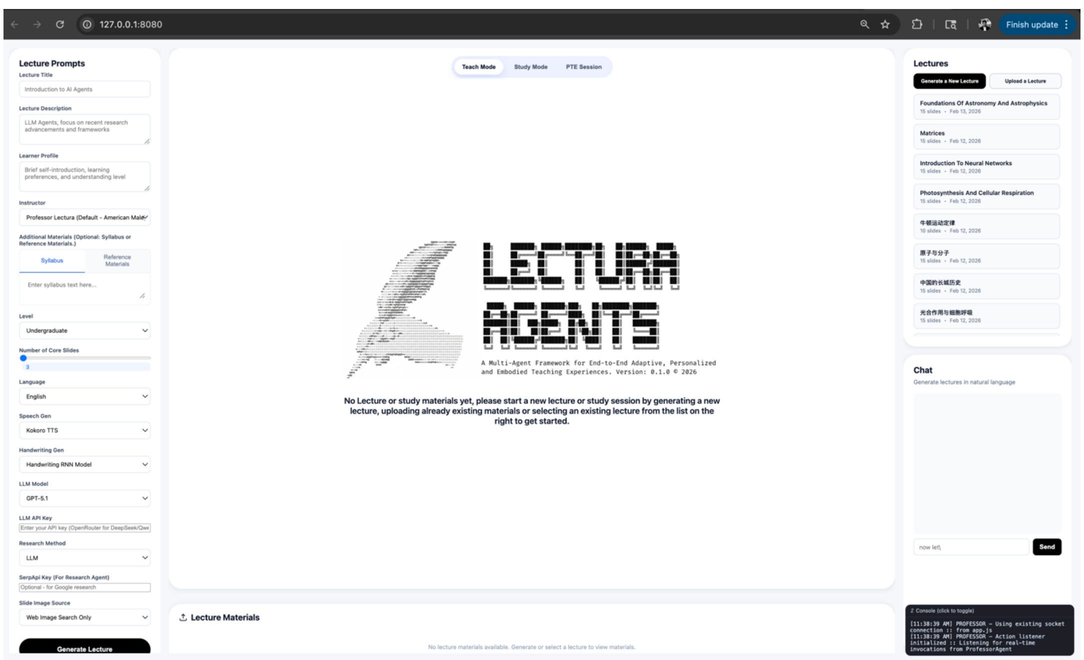

Figure 13: Frontend view (with no generated lecture)

This will open the teaching environment in your browser at: http://127.0.0.1:8080/. The page should look like Figure 13:

There will be a few already generated lectures in the right Lectures pane for you to quickly try or you can also generate new lectures through either the chat pane or in the left prompt pane. Generated lecture materials will appear below the slide as they are generated.

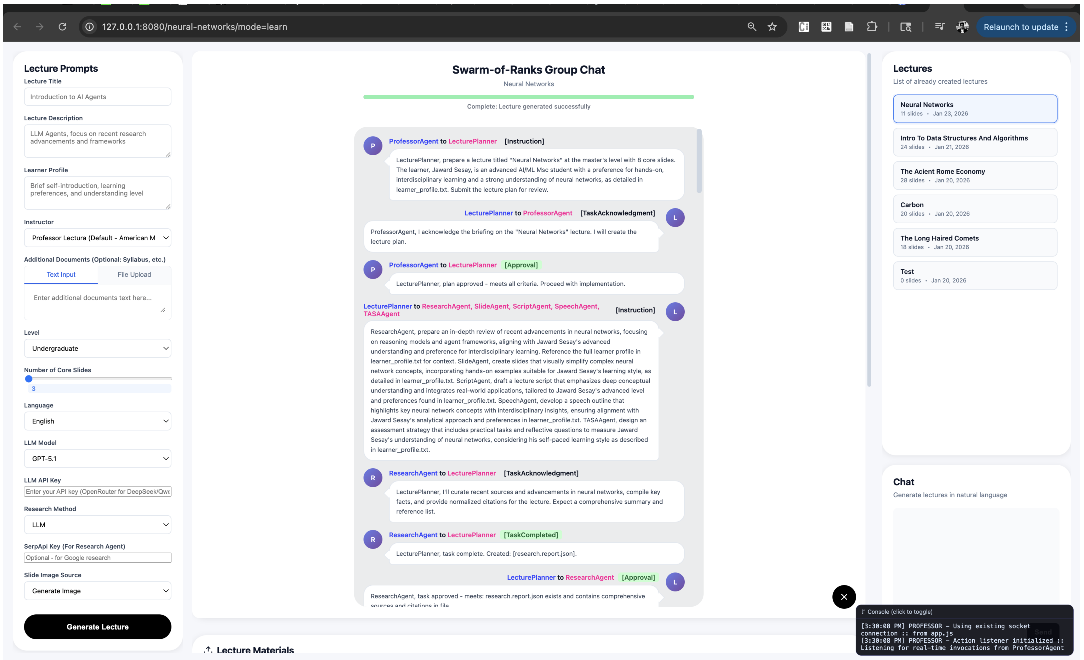

Figure 14: Swarm-of-Ranks group chat view (during lecture generation)

During lecture generation you can follow the whole process unfolds in real-time in the group chat session, as shown in Figure 14.

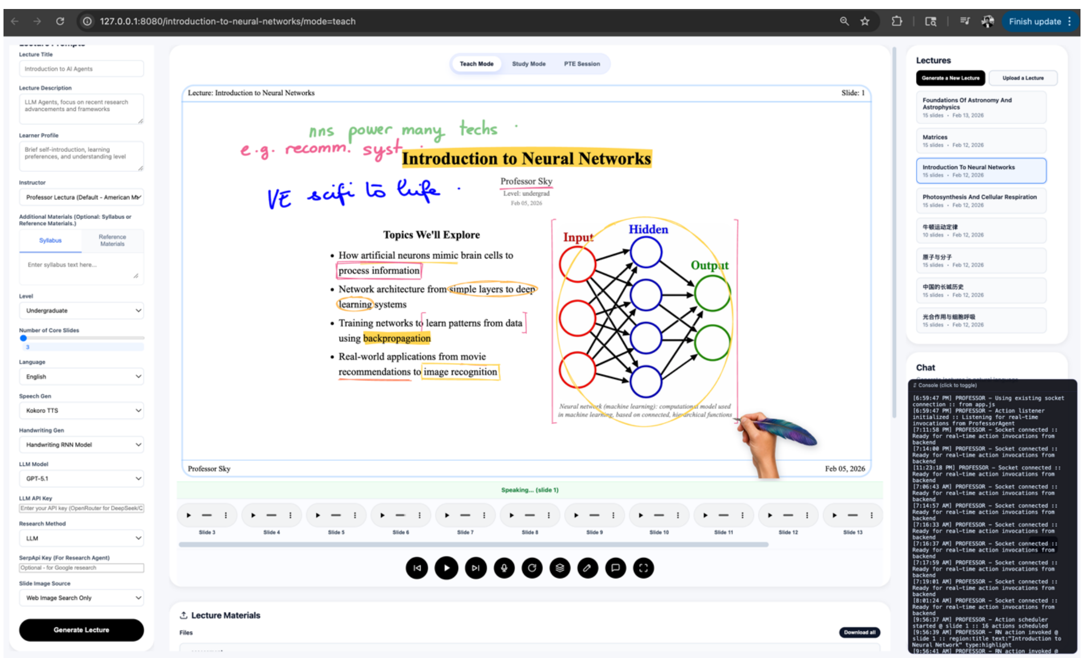

Figure 15: Teaching and learning environment (with teaching actions on lecture or study contents)

After lecture generation is complete, the view will automatically update with the slide deck (as shown in Figure 15). Below the deck are controls (Next, Play, Previous, Restart, Temporal Segmentation, and Chat).

4. If you wish to use the terminal for lecture generation, run this command:

*python3 lecture_prep.py *
*--lecture_title "Your Lecture Title Goes Here" *

*--lecture_desc "Describe the kind of lecture you want here" *
*--learner_profile "Add details about yourself, your learning preferences, and your current understanding level here" *
*--slides <enter desired number of core slides here> *
*--level <enter academic level: highschool, undergrad, masters, or phd> *
*--instructor_voice <choose desired instructor voice: professor_lectura, professor_sky, professor_isabella, etc.. > *
*--llm <select desired model here: gpt-5.1, gpt-4o, o3-pro, gemini-3-pro, gemini-flash-2.5-lite, claude-4.5, claude-4.1> *
*--research <enter research method: llm or google> *
*--language <enter output language: english, chinese, french, or spanish> *
*--speech_gen <choose speech backend: kokoro-tts, gemini-2.5-tts, or gpt-4o-mini-tts> *
*--handwriting_gen <choose handwriting mode: handwriting_rnn_model or preset_font_handwriting> *
*--slide_image <choose slide image mode: generate_only, generate_web_search, web_search_only, material_generate_alt, material_web_alt, or material_only> *
*--syllabus "Optional syllabus or curriculum text here" *
*--additional_materials "Optional reference text or path(s) to .pdf, .txt, or .md files, separated by commas" *
--data_root <optional custom output directory>

5. Example prompt:

   *python3 lecture_prep.py *
   *--lecture_title "Intro to Data Structures and Algorithms" *
   *--lecture_desc "A Computer Science lecture for a highschooler who likes basketball. Ensure covering these topics and more: 1. Introduction to Data Types and Abstraction 2. Introduction to Algorithms 3. Algorithm Vs Program. Understanding Data Structures 4. Abstract Data Types: (List, Set, Map, Priority Queue, Graph)" *
   *--learner_profile "Name: Taylor. Focus: Advanced Computer Science. Interests: Specialized algorithms, system design. Hobby: basketball. Learning style: Deep dive into technical details." *
   *--slides 24 *
   *--level highschool *
   *--instructor_voice professor_sky *
   *--llm gpt-5.2 *
   --research google

6. To view the generated lecture in the teaching environment run this command:

   python3 lecture_delivery.py --lecture <lecture folder name>

The folder could be, for example, *intro-to-data-structures-and-algorithms*.