

# Abstracting a Multi-Agent Framework for Next-Generation Educational Systems<sup>\*</sup>

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## Abstract

Recent progress in large language models, and intelligent agent systems is reshaping educational technology, shifting it from static tutoring applications toward adaptive, interactive, and scalable AI-based learning ecosystems. Yet, education continues to be a complex systems problem including lacking continuity across learning spaces, the current AI driven educational systems remain largely fragmented, most solutions rely on simplistic agent configurations with limited coordination mechanisms and insufficient governance structures, and most of the existing systems are typically confined to isolated learning contexts. To this end, this paper introduces SOFIA, a hierarchical multi-agent framework designed to maintain learning continuity across both classroom and home settings. The framework unifies collaborative and personalized learning in a single architecture, enabling coordinated learning experiences that extend beyond conventional classroom limits. SOFIA enables continuous monitoring and analysis of behavioral and contextual signals to anticipate learning challenges, shifting educational support from reactive interventions to proactive guidance. Furthermore, the system maintains persistent models of learners cognitive, behavioral, emotional, and contextual states to support long-term adaptation and personalization. The architecture implements hierarchical governance via a Supervisor–Broker Agent that coordinates agent interactions, ensures pedagogical coherence, and promotes system-level transparency and explainability. The design of SOFIA is driven by a set of research questions that examine existing approaches, identify their limitations, and motivate the need for integrated multi-agent educational frameworks. However, SOFIA offers a scalable, governance-aware, and learner-centered basis for next-generation educational systems that can provide continuous, adaptive, and context-aware learning support.

## Keywords

Multi-agent system, Agentic AI, Artificial Intelligence, Education,

## 1. Introduction

Education is undergoing a fundamental transformation driven by recent advances in Artificial Intelligence (AI), particularly in Generative AI and agent-based systems [1]. These technologies extend educational systems beyond static content delivery toward dynamic, context-aware, and learner-centric experiences [2, 3]. In parallel, Multi-Agent Systems (MAS) have gained increasing attention as a powerful paradigm for modeling complex and distributed educational ecosystems [4]. By enabling decentralized intelligence, collaboration, and adaptive coordination, MAS provide a strong foundation for next-generation learning platforms. Existing applications include intelligent tutoring agents, peer-learning simulations [5], collaborative problem solving environments, and personalized recommendation systems. Despite these advances, many MAS-based educational frameworks remain limited in terms of architectural scalability, coordination efficiency, and system-level intelligence [6]. Recent efforts have explored the integration of Multi-Agent Reinforcement Learning (MARL) with Generative AI to enhance the adaptability and pedagogical quality of AI-generated educational content [7]. However, current AI driven educational systems remain largely fragmented. Most solutions rely on simplistic

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agent configurations with limited coordination mechanisms and insufficient governance structures. Furthermore, these systems are typically confined to isolated learning contexts (e.g., classroom-only or home-only environments), lacking continuity across learning spaces. This fragmentation hinders the development of comprehensive learner models and limits the ability to provide proactive, long-term educational support. While the paradigm of Agentic AI introduces key concepts such as hierarchical control, persistent memory, and cross-context awareness, these capabilities are not yet fully realized in existing educational MAS architectures.

To address these challenges, this paper proposes a hierarchical, cross-context multi-agent framework designed to support continuous and proactive learning. The proposed architecture incorporates: (i) a *pedagogical meta-controller* for high-level governance and decision making, (ii) a *system orchestration layer* to coordinate agent interactions and workflows, and (iii) a *persistent memory layer* to enable long-term learner modeling. By bridging classroom and home learning environments, the framework aims to deliver a unified and adaptive educational ecosystem that supports both collaborative and individualized learning processes.

The development of this framework is guided by the following research questions:

- (RQ1) What are the existing multi-agent based solutions in the educational domain?
- (RQ2) What limitations characterize current approaches?
- (RQ3) How can these limitations be addressed through a novel multi-agent framework?

The remainder of this paper is organized as follows. Section 2 reviews related work on AI-driven educational systems and multi-agent learning paradigms, also analyzing the limitations of existing solutions. Section 3 presents the proposed framework and its main components and the implications of the proposed approach. Section 4 discusses future research directions, implementation perspectives, related to the proposed framework. Finally, Section 5 concludes the paper.

## 2. Literature Review

In the context of analyzing the application of MAS in the educational domain, there is an increasing research interest in their potential to transform learning environments. A wide range of studies have explored, implemented, and proposed MAS based frameworks aimed at enhancing educational processes and learner support. To systematically position this work, Section 2.1 reviews the state of the art in MAS driven educational systems, while Section 2.2 analyzes the limitations, challenges, and open issues of existing approaches, thereby motivating the need for the proposed framework.

### 2.1. Multi-Agent Systems and Agentic AI Frameworks for Educational Applications

Several existing studies have explored the integration of MAS within educational ecosystems. Among these, **Learning to Coordinate and Teach Roles (LeCTR)** [8] introduces a cooperative Multi-Agent Reinforcement Learning framework for learning-to-teach scenarios. In this approach, agents learn when to request advice, when to provide guidance, and what type of assistance to deliver without relying on expert supervision. Unlike traditional MARL methods that primarily focus on task completion, LeCTR emphasizes improving learning efficiency through coordinated agent interactions.

Recent work has explored the integration of graph based learning to capture relational dependencies in educational data. Singh et al. [9] propose a **hybrid MARL + Graph Neural Network (GNN)** framework for student employability prediction. The system models students as agents while representing course skill relationships as graph structures, enabling the capture of both individual performance and peer interactions. It is structured around three main components: (i) *graph-based feature modeling*, where GNNs generate embeddings encoding academic performance, skills, and interaction histories, (ii) *MARL-driven behavior optimization*, allowing agents to learn adaptive policies aligned with employability outcomes, and (iii) a *hybrid prediction architecture* that integrates relational embeddings with policy learning to improve prediction accuracy. This approach demonstrates the potential of combining relational reasoning with adaptive decision-making in educational systems.

Zhan et al. propose a **EduPlanner** [10] a Large Language Model (LLM) based multi-agent architecture for the automated generation, evaluation, and optimization of instructional design. The framework addresses the limitations of single LLM systems by orchestrating multiple specialized agents and modeling student competencies through a Skill Tree structure. Its design is based on three main components: (i) *knowledge background modeling* via multidimensional skill representation, (ii) *instructional design* evaluation using CIDPP criteria (Clarity, Integrity, Depth, Practicality, and Pertinence), and (iii) *iterative optimization* through evaluator feedback and error analysis.

Similarly, Wang and his colleagues introduce a **GenMentor** [11] focuses on goal oriented adaptive learning through MAS coordination. It supports (i) *skill gap identification* by aligning learning objectives with required competencies, (ii) *dynamic learner modeling* through continuous profile updates, and (iii) *personalized resource delivery* via adaptive content generation and learning path planning. Where **MultiTutor** [12] extends this direction by proposing a multi-agent LLM-based tutoring framework that enables personalized and multimodal learning support. The system coordinates specialized agents for knowledge generation, pedagogical scaffolding, and visual content creation, including expert agents, scaffolding agents, and visualization agents that enhance conceptual understanding.

Expanding beyond tutoring, **EduMAS** [13] introduces a knowledge driven MAS architecture that integrates specialized learning agents with graph-based knowledge navigation to improve reasoning and pedagogical effectiveness. Its contributions include (i) *task decomposition* through specialized agents, (ii) *graph-based knowledge* extraction to enhance contextual relevance, and (iii) *emotional awareness mechanisms* to support context sensitive pedagogical adaptation. In a complementary direction, **EduVerse** [14] presents a multi-agent educational simulation environment that supports customizable learning spaces and human in the loop agent configuration. It's *layered Cognition Interaction Evolution (CIE)* architecture enables the modeling of learner cognition, social interaction, and long-term behavioral evolution, facilitating realistic classroom simulations and adaptive human agent collaboration.

Another emerging line of research focuses on LLM-based learner simulation frameworks such as **EduAgent** [2] and **Agent4Edu** [15]. These systems generate cognitively plausible student behaviors through structured learner profiles, hierarchical memory representations, and chain of thought reasoning. Such simulated environments enable risk free experimentation, robustness testing, and systematic evaluation of tutoring strategies without deployment in real world settings. By capturing evolving learner states and misconceptions, they enhance explainability and support algorithmic validation. However, these approaches primarily function as experimental testbeds rather than fully integrated adaptive learning systems.

Beyond tutoring and simulation, Agentic AI represents a broader paradigm shift from linear prompt response interactions toward autonomous, multi step, workflow oriented orchestration. Conceptual frameworks such as **Agent4EDU** [16] classify educational agents according to their autonomy and interaction depth, illustrating the transition from passive assistants to collaborative cognitive partners. Workflow-based systems such as **Agentic Workflow for Education (AWE)** [17] and **AutoGen** [18] operationalize this paradigm through reflective planning loops, tool integration, role specialization, and swarm-based coordination. At the institutional level, agentic systems further extend AI capabilities to governance, decision support, and compliance monitoring through explainable and human in the loop mechanisms. In this context, **Laila AI** [19] exemplifies the application of agentic AI for administrative automation in higher education. The system adopts a low code, event driven architecture to automate institutional workflows while maintaining human oversight. It focuses on three key functions: (i) *administrative workflow automation*, enabling the execution of tasks such as faculty evaluations, dissertation screening, and KPI monitoring with significant reductions in processing time, (ii) *human in the loop governance mechanisms*, incorporating explainability, reviewer intervention, and bias auditing to ensure transparency and compliance, and (iii) *real-time strategic support* through predictive analytics, dynamic dashboards, and policy simulation tools. This approach highlights the extension of agentic AI beyond pedagogical applications toward institutional decision-making and governance.

Table 1 provides a comparative overview of existing multi-agent and agentic AI frameworks in education, illustrating their architectural characteristics, coordination strategies, and application focus, and revealing structural fragmentation across current approaches.

**Table 1**

Comparison of Multi-Agent and Agentic AI Frameworks in Education

| Ref  | MAS architecture                   | Core technologies                                                        | Agent type                                                     | Educational Use Cases                                            |
|------|------------------------------------|--------------------------------------------------------------------------|----------------------------------------------------------------|------------------------------------------------------------------|
| [8]  | Cooperative MARL architecture      | MARL, Actor Critic methods, Neural Networks                              | Teacher agents, Student agents                                 | Peer teaching, collaborative problem-solving                     |
| [9]  | Hybrid MARL architecture           | MARL, GNN, Deep learning                                                 | Student agents                                                 | Career guidance, skill planning                                  |
| [11] | LLM tutoring MAS                   | Large Language Models, learner modeling, recommendation algorithms       | Learner modeling agents, Content agents, Path planning agents. | Adaptive learning pathways                                       |
| [12] | LLM collaborative MAS              | LLM reasoning, multimodal generation                                     | Manager, Expert, Scaffolding, Visual, Resource agents          | STEM support, explanation refinement                             |
| [10] | LLM based multi-agent architecture | Large Language Models, Prompt engineering                                | Planner, Generator, Reviewer, Evaluator agents                 | Automatic lesson planning                                        |
| [2]  | Generative agent MAS               | LLM reasoning, cognitive modeling, behavioral simulation                 | Student behavior agents                                        | ITS evaluation, classroom simulation                             |
| [16] | Agentic workflow MAS               | LLM reasoning, MAS collaboration                                         | Educational service agents                                     | Educational AI system planning                                   |
| [17] | Workflow oriented MAS              | LLM agents, task planning, RAG                                           | Planning agents, Tool agents                                   | Autonomous tutoring pipelines                                    |
| [15] | Modular multi agent reasoning      | Hierarchical memory (short/long-term)                                    | Simulation and personalization                                 | Behavior modeling, data generation                               |
| [19] | Governance oriented MAS            | Agentic AI, predictive analytics                                         | Decision agents, Oversight agents, Workflow agents             | Administrative efficiency                                        |
| [18] | Conversational MAS framework       | LLM reasoning, multi agent dialogue coordination                         | Assistant agents, User prox                                    | Educational pipelines, tutoring systems                          |
| [14] | Simulation based MAS architecture  | LLM reasoning, cognitive modeling, human in the loop, long-term memory   | Teacher agents, Student agents                                 | Classroom simulation, behavior modeling, human agent interaction |
| [13] | Knowledge driven MAS architecture  | Graph based knowledge representation, LLM reasoning, affective computing | Specialized pedagogical agents                                 | Intelligent tutoring, adaptive learning, pedagogical reasoning   |

Referring to RQ1, the integration of MAS in educational environments has been explored through multiple complementary paradigms, reflecting the diversity of applications and technological approaches, including (i) A first line of research focuses on MARL-based educational systems, where agents learn adaptive teaching and learning strategies through interaction. Frameworks such as LeCTR [8] and hybrid MARL-GNN models [9] demonstrate how reinforcement learning can support decision-making processes, optimize learning strategies, and capture both individual and relational dynamics among learners. (ii) A second category includes LLM-based multi-agent architectures, where multiple specialized agents collaborate to support instructional design, tutoring, and content generation. Systems such as EduPlanner [10], GenMentor [11], and MultiTutor [12] highlight the role of agent specialization and coordination in delivering personalized, adaptive, and multimodal learning experiences. (iii) Another important direction is represented by simulation oriented MAS frameworks, including

EduMAS [13], EduVerse [14], and EduAgent [2]. These approaches focus on modeling learner cognition, social interaction, and behavioral evolution, enabling controlled experimentation, evaluation of pedagogical strategies, and analysis of classroom dynamics. (iv) Finally, recent advances in Agentic AI systems extend MAS beyond traditional tutoring and simulation toward autonomous, workflow oriented orchestration. Frameworks such as AWE [17], AutoGen [18], and Laila AI [19] demonstrate how agent-based systems can support not only learning processes but also institutional functions, including decision-making, governance, and administrative automation.

Overall, these studies illustrate that multi-agent systems have been extensively adopted across various layers of educational ecosystems, ranging from learning optimization and tutoring to simulation and institutional management. This widespread adoption highlights the strong potential of MAS as a foundational paradigm for next generation educational systems.

## **2.2. Limitations and Research Challenges in Existing Approaches**

Despite the significant progress achieved by existing approaches, several challenges remain that limit their effectiveness and scalability in real-world educational environments.

### **2.2.1. Identified Limitations**

Despite the rapid development of multi-agent and agentic AI approaches in education, current systems remain largely fragmented and task oriented rather than ecosystem oriented. Many frameworks focus on specific learning functions such as tutoring, curriculum planning, or learner simulation without ensuring continuity across learning environments. For example, tutoring centered systems including GenMentor [11], and MultiTutor [12], curriculum-design approaches including EduPlanner [10], and learner simulation platforms including EduAgent [2] and Agent4Edu [15] operate within isolated contexts rather than supporting integrated classroom and home learning experiences. Another limitation concerns the predominantly reactive nature of existing systems. Many approaches intervene only after performance degradation instead of anticipating learning difficulties. Reinforcement learning based strategies and predictive frameworks improve coordination or outcome estimation but rarely support proactive pedagogical adaptation [8, 9, 17, 18]. From an architectural perspective, current solutions often lack explicit governance and pedagogical control. Agents typically function as independent modules generating recommendations or content without coordinated oversight, escalation mechanisms, or educational alignment policies, leading to flat coordination structures and limited system transparency [19, 16]. Learner modeling also remains limited. Many systems rely on short-term representations of learner activity, while persistent cognitive and behavioral profiles supporting longitudinal adaptation are rarely maintained [10, 2, 15]. Finally, personalization strategies frequently optimize individual task performance without considering class level alignment or learning equity. This creates a gap between AI optimization objectives and pedagogical fairness requirements [20]. Overall, current systems provide powerful components but still lack an integrated architecture capable of coordinating collaborative and individual learning across contexts while supporting long-term and equitable learning progression.

Referring to RQ2, current multi-agent and agentic AI approaches in education remain limited by their fragmented and task specific nature. Existing systems lack a unified architectural perspective that integrates multiple learning contexts, supports proactive pedagogical adaptation, and ensures coordinated governance across agents. Moreover, the absence of persistent learner modeling and the limited consideration of fairness and group level alignment further constrain their effectiveness in real-world educational settings. These limitations highlight the need for a holistic, hierarchical, and cross-context multi-agent framework capable of orchestrating learning processes, ensuring continuity between classroom and home environments, and supporting long-term, equitable learner development.

### **2.2.2. General Contribution**

To address these gaps, we have proposed a hierarchical cross context proactive multi-agent educational ecosystem SOFIA designed to transform existing task oriented systems into integrated and adaptive

learning environments. As illustrated in Fig. 1, the proposed framework directly responds to the fragmentation, reactive intervention strategies, weak longitudinal modeling, and flat coordination observed in current approaches. The primary objective of this work is to support learning continuity beyond the classroom and to shift educational systems from reactive correction mechanisms toward proactive and preventive learning support. The framework introduces a coordinated multi-agent architecture that continuously monitors learner behavior, interaction patterns, and contextual signals in order to anticipate potential learning difficulties and orchestrate timely, pedagogically aligned interventions. Specifically, the proposed system aims to:

- Ensure learning continuity between classroom collaboration and home-based personalization through a shared learner memory.
- Transform education from reactive intervention to proactive adaptation by anticipating risks before performance degradation occurs.
- Balance collective classroom learning with individualized support in home environments.
- Reduce learning gaps and progressively align all learners with expected class-level mastery.
- Provide governed and explainable AI assistance aligned with pedagogical objectives and institutional policies.
- Maintain persistent, longitudinal learner profiles incorporating cognitive, behavioral, emotional, and contextual dimensions.

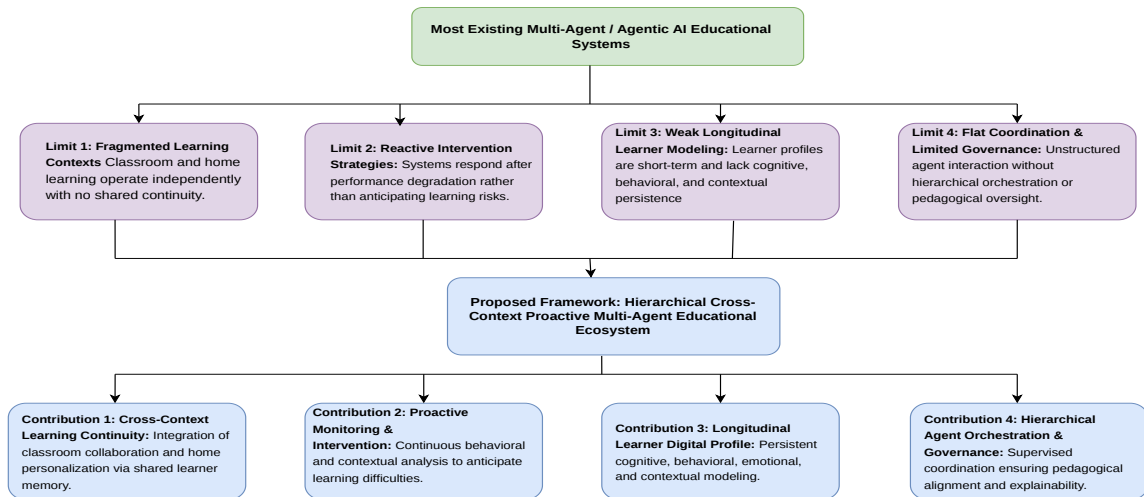


**Figure 1:** Structural Limitations of Educational AI Systems and Proposed Framework Contributions.

### 3. SOFIA: A Hierarchical Learning Intelligence Architecture

To manage the complexity of educational interactions across multiple environments, actors, and time scales, the proposed framework is structured as a Hierarchical Multi-Agent System (HMAS) (Figure 2). This hierarchical organization enables clear separation of responsibilities, scalable coordination, and governed decision making across the entire learning ecosystem. The HMAS integrates human agents and machine agents within a unified, multi-level control structure. Each level operates at a different granularity of decision-making, while remaining tightly coupled through shared memory and feedback loops.

Unlike existing educational multi-agent systems that primarily focus on isolated tutoring, simulation, or workflow automation tasks, SOFIA introduces a unified hierarchical architecture that explicitly integrates governance, orchestration, cross-context continuity, and persistent learner modeling within

a single ecosystem. The novelty of the proposed framework does not lie in individual tutoring agents themselves, but rather in the coordinated integration of classroom collaboration, home-based personalization, proactive intervention, and policy-driven orchestration through a shared longitudinal learner representation. By combining these dimensions within a hierarchical multi-agent structure, SOFIA aims to support continuous, adaptive, and pedagogically aligned learning across educational contexts.

The proposed HMAS is organized into three main hierarchical levels, supported by a shared memory layer including (i) *Level 0 – Supervisor-Broker Agent* : Responsible for global supervision, policy enforcement, and high-level pedagogical decisions. (ii) *Level 1 – System Orchestration Layer* : Manages workflows, monitors learner behavior, and coordinates agent interactions across environments. (iii) *Level 2 – Learning Environments* : Includes the Classroom Environment and the Home Environment, where direct learning interactions occur. (iv) *Shared Memory and Learner Profile* : Maintains a persistent and evolving learner representation accessible across all levels.

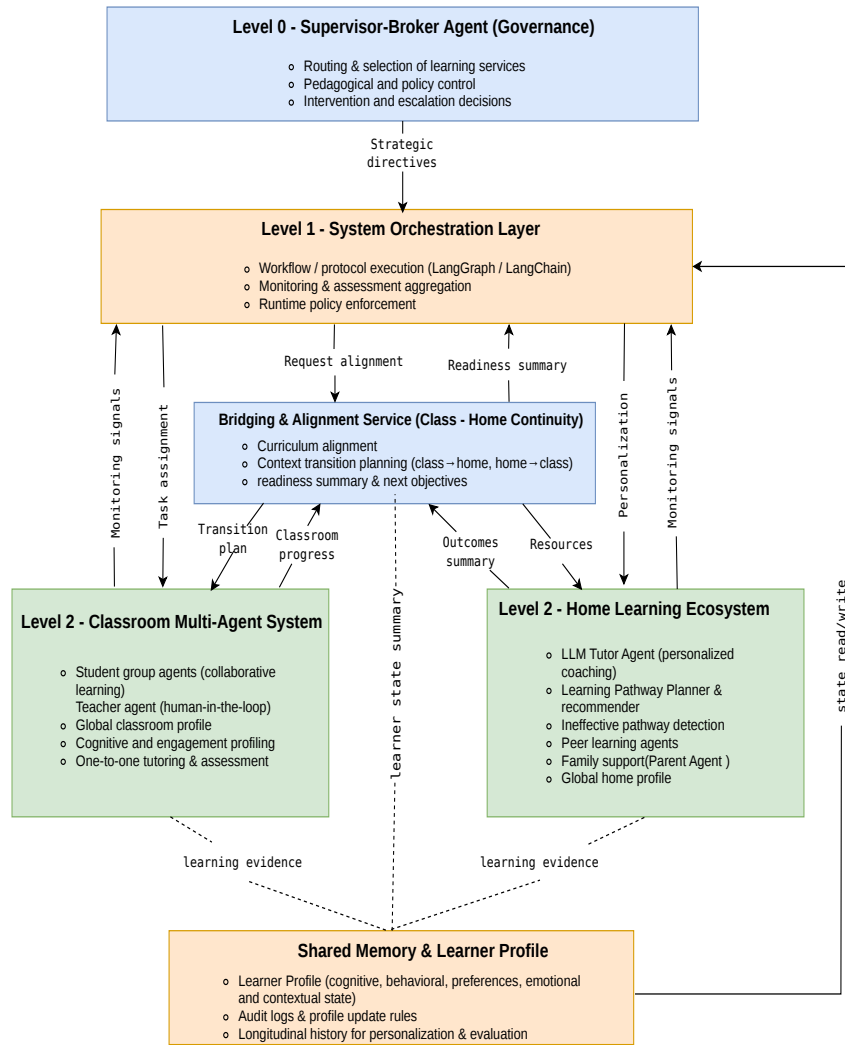


Figure 2: Global architecture.

### 3.1. Hierarchical Multi-Agent Architecture

To address the limitations of fragmented and context-isolated educational AI systems, we propose a HMAS that integrates governance, orchestration, and learning environments into a unified architecture.

The proposed system is structured across multiple hierarchical levels, enabling coordinated decision-making, adaptive learning, and continuous alignment between classroom and home contexts.

### 3.1.1. Level 0: Supervisor-Broker Agent (Governance Layer)

At the top of the hierarchy, the Supervisor–Broker Agent acts as a pedagogical meta-controller responsible for *global governance* and *strategic oversight*. This component is responsible for maintaining alignment between system-level behaviors, institutional policies, pedagogical objectives, and ethical constraints. Specifically, the Supervisor–Broker Agent regulates the overall behavior of the system by enforcing high-level policies governing AI usage, safety, and compliance. It supervises the coherence between classroom-based collaborative learning and home-based personalized learning, ensuring consistency in learning objectives, progress tracking, and intervention strategies across contexts. In addition, it supports high-level decision-making by identifying situations that require intervention (e.g., persistent learner difficulties or disengagement) and escalating them to human teachers when necessary. Beyond governance, this agent also plays a brokerage role by facilitating coordination among agents. It dynamically selects peer collaborators, learning resources, and support services by analyzing learner profiles, contextual signals, engagement indicators, and pedagogical objectives.

Operationally, the Supervisor-Broker Agent follows an event-driven orchestration strategy. Educational agents continuously generate behavioral, contextual, and performance-related signals, which are propagated through the orchestration layer using structured message-passing protocols. The Supervisor-Broker Agent maintains aggregated learner-state representations and continuously monitors coordination events generated across classroom and home environments. Based on these signals, it applies policy-based routing and decision rules to determine whether the system should trigger adaptive tutoring, peer collaboration, pathway re-planning, or escalation to human teachers. This orchestration mechanism enables coordinated system-level decision making, asynchronous agent interaction, and adaptive intervention while preserving controlled agent autonomy and pedagogical alignment.

### 3.1.2. Level 1: System Orchestration Layer

The System Orchestration Layer represents the operational core of the HMAS, translating high-level governance directives into executable learning processes. This layer coordinates agent interactions, monitors learner behavior, and enforces runtime constraints to ensure adaptive and context-aware learning. At its core, the orchestration layer is composed of three main components:

- **Workflow Engine.** The Workflow Engine manages the execution of agentic learning workflows by dynamically coordinating interactions among student agents, tutoring agents, assessment modules, and feedback mechanisms. Unlike static pipelines, it enables *adaptive* and *stateful workflows* that evolve according to learner progress and contextual signals. It supports dynamic agent selection, conditional execution, iterative refinement, and escalation to human teachers when required.
- **Behavior & Assessment Module.** This module continuously monitors learner interactions and performance across environments to generate real-time indicators of learner state, including engagement, difficulty, and mastery. These indicators serve as control signals that inform both workflow adaptation and higher-level decision-making. The extracted information is propagated to the Workflow Engine for dynamic adjustment and to the Supervisor–Broker Agent for strategic intervention.
- **Policy Engine.** The Policy Engine enforces runtime governance by constraining agent behaviors during execution. It ensures alignment with curriculum objectives, fairness and inclusivity requirements, and safety constraints. Acting as a control boundary, it can block, modify, or redirect agent actions when violations occur, thereby maintaining accountability and compliance throughout the system.

### 3.1.3. Bridging & Alignment Service

To ensure continuity across learning environments, the architecture incorporates a Bridging & Alignment Service as a cross-cutting component. This service does not introduce additional decision authority but operationalizes orchestration decisions by *translating learner states and objectives into context-aware actions*. It is responsible for aligning curriculum objectives across classroom and home settings, managing transitions between contexts, generating readiness summaries, and coordinating learning resources. By maintaining this separation from the hierarchical control structure, the system preserves architectural clarity while ensuring seamless learning continuity.

### 3.1.4. Level 2: Classroom Multi-Agent System

The Classroom Multi-Agent System represents the collaborative learning environment where structured, teacher-guided interactions take place. This layer supports *real time monitoring, group collaboration, and individualized support* within a supervised setting. Students are organized into collaborative groups of agents that engage in problem solving and project based activities, enabling both intra-group and inter-group knowledge exchange. A Teacher Agent, representing the human teacher, provides supervision, guidance, and validation of learning processes, while also serving as the primary escalation point for complex cases. In parallel, cognitive and engagement profiling mechanisms continuously construct learner representations based on performance, participation, and interaction patterns. These profiles support both group level dynamics and individualized interventions. Additionally, one to one tutoring and assessment mechanisms enable personalized feedback and mastery evaluation within the classroom context. The classroom environment generates structured evidence related to learner behavior, cognition, and engagement. This information contributes to a Global Classroom Profile, which informs higher-level orchestration and governance decisions.

### 3.1.5. Level 2: Home Learning Ecosystem

Complementing the classroom environment, the Home Learning Ecosystem supports *personalized and self-regulated learning* beyond formal instructional settings. This environment enables continuous learning while maintaining alignment with system-wide objectives. At its core, an LLM-based Tutor Agent provides adaptive, conversational support tailored to the learner's cognitive and emotional state. A Learning Pathway Planner constructs and updates personalized learning trajectories, recommending resources and activities based on learner progress and long-term goals. To ensure effectiveness, the system incorporates mechanisms for detecting suboptimal learning pathways and triggering adaptive interventions, such as resource reallocation or escalation. Peer Learning Agents facilitate collaborative revision, while a Parent Agent supports motivation and organization at the family level without compromising learner autonomy.

### 3.1.6. Shared Memory Layer and Global Profiles

At the foundation of the HMAS lies the Shared Memory Layer, which serves as a persistent and unified knowledge repository. This layer maintains learner profiles, interaction histories, behavioral patterns, and longitudinal learning records across all environments. Based on this information, the system constructs Global Profiles, including both classroom-level and home-level representations. The Shared Memory Layer enables (i) *adaptive workflow orchestration* through informed decision-making, (ii) *governance and intervention* at the supervisory level, and (iii) *personalized learning* support across environments.

The Shared Memory Layer maintains synchronized learner representations across classroom and home environments through continuous state updates generated by interacting agents. The memory structure combines short-term interaction histories with persistent longitudinal learner profiles, enabling contextual continuity, adaptive personalization, and historical reasoning across learning sessions.

### 3.2. Discussion

The proposed hierarchical cross context multi-agent framework represents a shift from isolated, task specific educational AI systems toward a more integrated and governed learning ecosystem. However, its practical realization raises several important considerations related to *scalability*, *predictive intelligence*, and *system governance*. From a scalability perspective, integrating classroom and home environments through a shared learner memory introduces architectural complexity, as coordinating multiple agents across contexts requires efficient workflow orchestration and well defined communication protocols. While hierarchical governance through the Supervisor-Broker Agent mitigates coordination challenges commonly observed in flat multi-agent systems, it also introduces computational and coordination overhead, highlighting the need for scalable orchestration strategies, distributed agent execution, and resource aware policy management for large scale educational deployments. In addition, enabling proactive educational support requires reliable detection of early learning risk signals. Although the current framework incorporates behavioral and cognitive monitoring mechanisms, the effectiveness of proactive intervention depends on robust predictive modeling techniques. Finally, *governance*, *fairness*, and *explainability* remain central challenges in agentic educational systems. While the proposed architecture introduces explicit governance through hierarchical orchestration and policy enforcement, balancing autonomy and control is essential. Excessive automation may reduce human agency, while insufficient oversight may result in biased or misaligned recommendations. Ensuring fairness across diverse learner profiles, maintaining transparency in intervention decisions, and preserving teacher oversight therefore remain critical requirements for the responsible deployment of such systems.

Referring to RQ3, SOFIA contributes a hierarchical, cross context multi-agent framework that addresses the key limitations identified in current approaches. Unlike existing task specific systems, the proposed framework introduces a unified architecture that integrates collaborative classroom learning and personalized home learning within a coherent ecosystem. It enables proactive educational support through continuous learner monitoring and adaptive orchestration, moving beyond reactive intervention strategies. Furthermore, the framework incorporates explicit governance through the Supervisor-Broker Agent and policy-driven orchestration, ensuring alignment with pedagogical objectives, ethical constraints, and institutional requirements. By leveraging persistent learner modeling through a shared memory layer, the system supports long-term personalization and continuity across learning contexts. Overall, the proposed approach provides a scalable, governance-aware, and learner-centric foundation for next-generation educational systems capable of coordinating multi-agent interactions across environments while supporting continuous and equitable learning.

## 4. Future Research Directions

Although the proposed SOFIA framework provides a structured architecture for intelligent educational orchestration, several research avenues remain open to further enhance its capabilities and facilitate real-world deployment. From a technical perspective, future work could focus on embedding adaptive learning mechanisms into the agent ecosystem, particularly through MARL approaches that enable agents to continuously refine their coordination strategies-based on learner progress, engagement trajectories, and collaboration patterns. This direction would support a transition from predominantly rule-based orchestration toward more experience-driven adaptation. From a human-centered AI perspective, future research may investigate the integration of Reinforcement Learning from Human Feedback to incorporate teachers' expertise and pedagogical judgment directly into agent decision-making processes, thereby improving alignment with authentic instructional practices while enhancing transparency and trustworthiness.

From a pedagogical perspective, future studies could explore how hierarchical multi-agent orchestration can better balance individualized learner support with broader classroom objectives. Particular attention may be given to proactive intervention strategies capable of identifying early indicators of learning difficulties and providing timely support before measurable performance degradation occurs.

While the current work primarily focuses on the conceptual and architectural foundations of SOFIA,

the framework is intentionally designed to remain compatible with existing agentic AI and multi-agent orchestration technologies. From an implementation perspective, the proposed framework can be operationalized through existing orchestration and conversational agent frameworks. Multi-agent coordination may be supported through frameworks such as AutoGen, enabling structured communication, message passing, and role-based interaction among educational agents. Stateful workflow execution and adaptive routing mechanisms may be implemented using graph-based orchestration frameworks such as LangGraph, supporting event-driven coordination, conditional task execution, and dynamic workflow transitions based on learner states. In addition, learner simulation environments such as Agent4Edu could support the modeling of personalized learner behaviors and enable large-scale experimentation before deployment in real educational settings. Persistent learner memory may further rely on hybrid storage architectures combining structured learner profiles, vector-based long-term memory representations, and synchronized contextual state management across classroom and home environments. Although the present work does not yet provide a full implementation, these technologies provide a practical technological foundation for future realization, simulation, and validation of SOFIA.

From the perspective of system deployment, future work should aim to validate SOFIA through both simulation-based experimentation and pilot educational deployments. Initial validation could rely on simulated learner environments and conversational multi-agent orchestration platforms to evaluate coordination efficiency, proactive intervention strategies, adaptation quality, and cross-context learner continuity. Longitudinal analyses in real educational settings could further assess how maintaining continuity across classroom and home environments influences learner engagement, knowledge retention, collaboration quality, and personalization effectiveness. Finally, future research might focus on developing robust evaluation frameworks that integrate educational indicators (e.g., learning gains, engagement, equity) with multi-agent system metrics (e.g., coordination efficiency, scalability, orchestration latency, adaptation quality, and governance compliance) in order to comprehensively assess the effectiveness of intelligent educational MAS architectures.

## 5. Conclusion

This paper presented SOFIA, a hierarchical multi-agent framework designed to support continuous and coordinated learning across classroom and home environments. The proposed system integrates collaborative, classroom-based learning with personalized, home-based learning within a unified architecture governed by a global orchestration and control layer. By leveraging MAS, SOFIA enables a transition from reactive educational systems toward proactive and adaptive learning ecosystems. In particular, the framework supports learning continuity beyond traditional classroom boundaries by coordinating in-class and at-home learning processes in a coherent and context aware manner. It effectively balances collective learning objectives with individualized learning needs, thereby bridging collaborative and personalized learning paradigms.

Furthermore, SOFIA incorporates long-term learner modeling through persistent student profiles, enabling continuous adaptation, informed decision making, and personalized support over time. Through this unified approach, the framework provides a scalable foundation for next generation educational systems that are adaptive, context-aware, and learner centric.

## Declaration on Generative AI

The authors have not employed any Generative AI tools.

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