Research on Personalized Learning Systems Driven by Multi-Agent Collaboration

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Abstract. Multi-agent collaboration provides a scalable solution for personalized learning path generation, tackling the long-standing challenge of adaptive instruction. Although previous research has improved agent functions and learner modeling, the integration of Socratic dialogue mechanisms remains underexplored. To address this gap, this paper presents a framework that unifies learner profiling, multi-agent collaboration, and dynamic path generation. A dynamic learner state vector is constructed to represent knowledge mastery, cognitive depth, and engagement. Four specialized agents—cognitive diagnosis, question generation, metacognitive regulation, and path evolution—work together to guide instructional decisions. Central to the framework is a Socratic dialogue engine that leads learners through a three-tiered question chain (clarification, probing, and refutation) to stimulate cognitive conflict and foster higher-order thinking. The proposed approach is both theoretically grounded and practically implementable. Its feasibility is demonstrated through algorithmic specifications and simulated learner trajectories, showing clear potential for real-world deployment in intelligent tutoring systems.

Keywords: Profiling, Multi-Agent Collaboration, Socratic Dialogue, Personalized Learning Path, Cognitive Advancement

1 Introduction

Building on a three-dimensional learner profiling framework, this study aligns with the principles of personalized learning, emphasizing individualized cognitive development in AI-enhanced education [1]. Policy initiatives such as China Education Modernization 2035 advocate leveraging information technology to integrate large-scale education with personalized learning [2]. Advances in generative AI, multimodal sensing, and multi-agent systems provide opportunities for scalable, deeply personalized learning pathways [3]. However, existing approaches often focus on question scaffolding[4], dialogue design[5-6], or task allocation [7-8] without systematically inducing cognitive conflict, guiding reasoning, or promoting learner-centered cognitive growth[9].To address these limitations, this study proposes an agent-driven framework that integrates Socratic dialogue with dynamic learner profiling for personalized learning path generation. By prioritizing cognitive guidance over static content deliv-

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ery, the framework enhances reasoning depth, conceptual understanding, and learner engagement, providing a theoretically grounded and practically scalable solution.

2 Multidimensional Modeling Mechanism of Learner Profiling

2.1 Multidimensional Data Structure of Learner Profiling

Building on a three-dimensional learner profiling framework (learning process, engagement, outcomes) [10], this study integrates metacognitive regulation and Socratic dialogue to establish a cognitive development loop. In the learning process dimension, structured, natural language, and multimodal affective data capture learners' knowledge, reasoning, and strategy use. The engagement dimension incorporates multimodal signals—facial expressions, vocal tone, interaction tempo, and eye-tracking—to monitor cognitive construction, affect, and self-regulation [11]. The outcomes dimension evaluates performance, conceptual mastery, and transfer ability through multidimensional assessment based on multiple intelligence theory [12], providing interpretable feedback for path adjustment. Deviations in performance trigger metacognitive monitoring, prompting strategy reflection and behavioral adaptation. Through dynamic interaction, behavior influences outcomes, engagement regulates cognitive depth, and outcomes guide both process and engagement. This three-dimensional coupling, sustained by Socratic dialogue, forms a closed loop that supports coherent cognitive development and personalized learning path generation.

2.2 Data Processing and Learner Profiling Pipeline

After collecting multi-source data, preprocessing and normalization—including missing value imputation, anomaly labeling, duplicate removal, and format standardization—ensure data reliability. Raw logs of learning behaviors, interactions, and affective signals are heterogeneous and temporally structured; they are reconstructed into time-indexed matrices:

$$B = [b_{i,j}(t)], i \in \text{learners}, j \in \text{features}, t \in \text{time steps} \tag{1}$$

where each element represents a standardized behavioral or affective measurement. Feature extraction integrates statistical metrics, NLP embeddings, and multimodal fusion to encode knowledge, cognitive, dialogue, and engagement signals. These features are embedded into a dynamic learner state vector:

$$S(t) = [K(t), C(t), E(t)] \tag{2}$$

where $K(t)$ denotes knowledge mastery, $C(t)$ represents cognitive processing depth, and $E(t)$ captures engagement and affect. The vector updates iteratively ($S(t) \rightarrow S(t+1)$) to reflect evolving cognitive trajectories. The SOLO level $C(t) \in \{1,2,3,4,5\}$ is updated after each dialogue based on learner response quality $q \in [0,1]$ and question difficulty $d \in [0,1]$, using threshold θ (e.g., 0.6)

$$C(t+1) = \min(5, C(t) + \left\lfloor \frac{q \cdot d}{\theta} \right\rfloor) \tag{3}$$

where θ is a threshold parameter (e.g., 0.6).

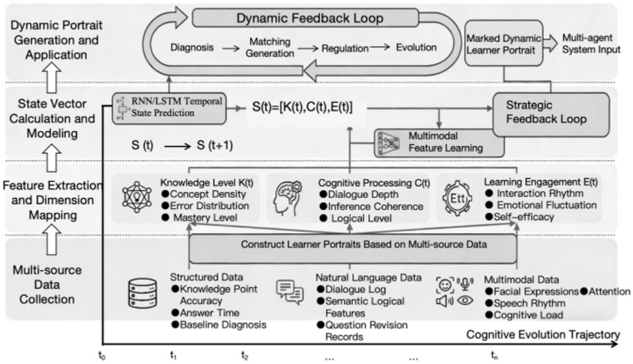

Fig. 1. Learner Profiling Modeling Mechanism.

Clustering methods (e.g., K-means) generate labeled learner profiles, forming dynamic representations (see Figure 1). Multimodal data integration enables temporal state modeling, coupling behavior, cognition, and affect within a unified space.

3 Multi-agent Collaboration Mechanism

Building on the dynamic learner state vector S(t), this study proposes a hierarchical, cognition-oriented multi-agent decision-making framework. Each agent performs specialized functions within a shared state space, and their collaborative operation enables a mechanism shift from "information matching" to "cognitive reconstruction." The system centers on learners' cognitive development and differentiates functions across four agent types—diagnosis, question generation, metacognitive regulation, and path evolution—forming a systematic collaborative mechanism.

The Cognitive Diagnosis Agent serves as the preliminary decision-making module. It integrates knowledge structure indicators such as knowledge point accuracy, error distribution, and concept connectivity, and applies the SOLO taxonomy to identify learners' developmental stages and potential cognitive gaps.

Based on the diagnostic results, the Question Generation Agent designs a progressive sequence of problems tailored to the learner's current cognitive level. Following Socratic questioning principles, it advances through "clarification → follow-up → refutation," dynamically adjusting difficulty according to learners' dialogue responses, guiding learners from surface comprehension to deep reasoning.

The Metacognitive Regulation Agent monitors indicators such as attention and emotional fluctuation throughout the learning process. When confusion or cognitive stagnation is detected, it adjusts questioning pace and resource allocation, thereby supporting learners' self-regulation and enhancing cognitive processing depth.

The Path Evolution Agent oversees overall generation and optimization of the learning path. It continuously updates and refines the learning sequence. By analyzing trends in S(t) and leveraging cognitive conflicts arising in dialogue, the system dynamically plans task difficulty and resource distribution, ensuring alignment of the learning path with learners' evolving cognitive state.

4 Personalized Learning Path Generation Mechanism

Personalized learning path generation is formulated as a dynamic, iterative process driven by continuous interaction between learner states and instructional responses. Rather than following predefined sequences, the path evolves in accordance with changes in the learner's cognitive state.

The process begins with the identification of the learner's current state S(t), which captures knowledge mastery, cognitive depth (SOLO level), and engagement state. This composite state determines both the starting point of the learning path and the initial difficulty level of instructional tasks. Learners with low mastery but high engagement receive entry-level conceptual tasks, while those with moderate mastery but shallow cognitive depth are directed toward probing questions rather than new content. In this way, the path is individually calibrated from the very first step rather than being uniformly applied.

Unlike conventional systems that advance learners upon correct answers, the present framework uses adaptive dialogue as the primary engine of progression. As the learner responds to Socratic questions, the system continuously evaluates not only answer correctness but also reasoning consistency and explanatory depth. When a reasoning gap or contradiction is detected—for example, a learner answers a conceptual question correctly but fails to justify it or gives conflicting answers to logically related questions—the system deliberately introduces a cognitive conflict prompt, such as a refutation question. This prompt does not simply inform the learner of an error but invites the learner to resolve the inconsistency. Only when the learner successfully articulates a coherent resolution does the system advance to a higher level of abstraction or difficulty. Thus, progression is contingent not on performance per se but on demonstrated cognitive restructuring.

The learning path is strictly non-linear and permits backward moves. When a learner encounters persistent difficulty—for instance, failing to resolve the same type of cognitive conflict after multiple attempts or showing declining engagement during questioning—the system does not continue advancing. Instead, it invokes a scaffolding protocol: task difficulty is reduced, the question type reverts from refutation to probing or from probing to clarification, and supplementary explanatory prompts are inserted. This backward transition prevents learner frustration and consolidates prerequisite reasoning structures before re-attempting advancement. Such regressions are recorded as normal path dynamics rather than failures, and the system resumes forward progression once stable performance is re-established.

Throughout this process, the metacognitive regulation agent continuously monitors engagement signals, such as response latency, affective cues, or interaction rhythm. If cognitive stagnation is detected—characterized by repetitive incorrect responses without variation or prolonged hesitation—the agent temporarily overrides the default progression logic. It may reduce question complexity, switch to a different knowledge domain to restore confidence, or insert metacognitive prompts (e.g., "What strategy were you using just now?"). This intervention resets the learner's cognitive state without discarding the path history, after which the path evolution agent resumes normal operation from the adjusted state.

The learning path terminates when the learner's cognitive depth reaches the target SOLO level for a predefined set of core concepts, provided that engagement remains above a minimum threshold and the learner can consistently resolve refutation questions without scaffolding. In practice, this convergence is not a binary event but a sustained region of stable high-level performance, at which point the system outputs a final learning path summary and transitions to review or assessment mode. In summary, the personalized learning path is not a fixed sequence retrieved from a repository but a continuously reconstructed trajectory whose next step depends jointly on current knowledge, cognitive depth, engagement, and the learner's demonstrated ability to resolve cognitive conflict. This mechanism ensures that progression is always aligned with the learner's genuine cognitive readiness rather than superficial response correctness.

5 Conclusion

This study proposes a multi-agent–driven framework for personalized learning path generation that integrates dynamic learner profiling with Socratic dialogue. The results demonstrate that modeling learner states through knowledge, cognition, and engagement enables adaptive and continuous path evolution. The coordinated functions of cognitive diagnosis, question generation, metacognitive regulation, and path evolution agents effectively support cognitive progression by inducing structured inquiry and cognitive conflict. These findings suggest that shifting from content recommendation to cognition-oriented guidance enhances learning depth and engagement. The framework provides a scalable and theoretically grounded approach for intelligent education systems, offering implications for future research on adaptive learning and human–AI collaborative instruction.

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