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ABSTRACT

Reproducing cognitive development, group interaction, and long-term evolution in virtual classrooms remains a core challenge for educational AI, as real classrooms integrate open-ended cognition, dynamic social interaction, affective factors, and multi-session development rarely captured together. Existing approaches mostly focus on short-term or single-agent settings, limiting systematic study of classroom complexity and cross-task reuse. We present **EduVerse**, one of the first *user-defined* multi-agent classroom simulator supporting customizable environment, customizable agents, and multi-session evolution. A distinctive human-in-the-loop interface further allows real users to join the space. Built on a layered **CIE** (Cognition–Interaction–Evolution) architecture, EduVerse ensures individual consistency, authentic interaction, and longitudinal adaptation in cognition, emotion, and behavior—reproducing realistic classroom dynamics with seamless human–agent integration. We validate EduVerse in middle-school Chinese classes across three text genres, environments, and multiple sessions. Results show: **(i) Instructional alignment:** simulated **Initiate-Response-Feedback (IRF)** rates (0.34–0.55) closely match real classrooms (0.37–0.49), indicating pedagogical realism; **(ii) Group interaction and role differentiation:** network density (0.27–0.40) with about one-third of peer links realized, while human–agent tasks indicate a balance between individual variability and instructional stability; **(iii) Cross-session evolution:** the positive transition rate R^+ increase by 11.7% on average, capturing longitudinal shifts in behavior, emotion, and cognition and revealing structured learning trajectories; **(iv) Cross-disciplinary generalization:** without any additional tuning, IRF rates and peer-interaction topologies naturally adapt to the discourse characteristics of history instruction while preserving the core instructional structure, demonstrating robust cross-disciplinary transfer. Overall, EduVerse balances realism, reproducibility, and interpretability, providing a scalable platform for educational AI. The system will be open-sourced to foster cross-disciplinary research.

1 INTRODUCTION

A central challenge in human-centered AI is to simultaneously reproduce cognitive development, group interaction, and long-term evolution within virtual environments (Wang et al., 2024c; Parisi et al., 2019; Zheng et al., 2024; Chen & Liu, 2018; Zheng et al., 2025). While large language models (LLMs) excel at language understanding and immediate task completion, most research remains confined to static tasks or short-term interactions, falling short of capturing evolving cognition, stable behavioral styles, and socially dynamic processes (Maharana et al., 2024; Wang et al., 2025a; Tan et al., 2025; Li et al., 2025a). Similarly, multi-agent systems have primarily targeted structured games or fixed collaboration, lacking frameworks that support developmental agents whose cognition, personality, and social relations evolve naturally over time (Wang et al., 2024b; Ashery et al., 2024).

Educational settings, particularly classrooms, offer a natural testbed for modeling cognition, social interaction, and instructional feedback (Hattie & Timperley, 2007a; Poropat, 2009; Johnson et al., 1998). For example, Chinese language classes feature open-ended tasks, emotional nuance, and rich role-based interactions, ideal for studying development and group dynamics. Yet most intelligent tutoring systems and dialogue agents treat students as static performers (Anderson et al., 1995;

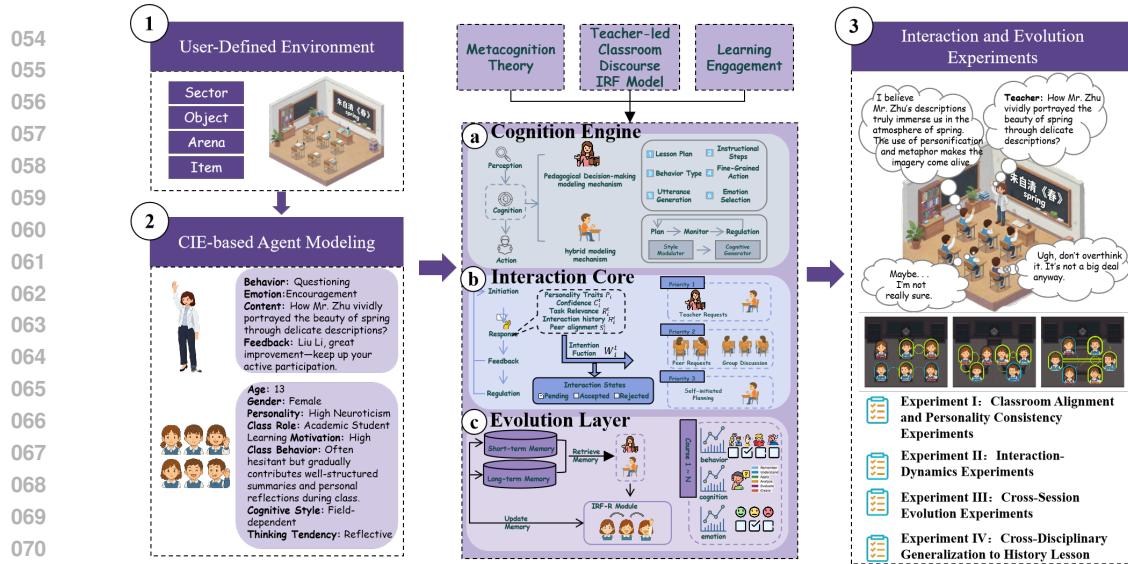


Figure 1: **Overview of EduVerse.** EduVerse comprises: (i) user-defined environment configuration; (ii) CIE-based agent modeling for teacher and student agents; (iii) interaction and evolution experiments spanning instructional alignment, group interaction, cross-session development, and cross-disciplinary generalization. Together, these components form a scalable, interpretable, and transferable multi-agent simulation platform for educational AI.

Nye et al., 2014; Lin et al., 2023), lacking persistent learner modeling, role-sensitive interaction, or longitudinal adaptation.

To overcome these limitations, we introduce **EduVerse**, one of the first *user-defined* multi-agent simulation space that supports environment customization through flexible physical layouts and seating arrangements, agent customization via a human-in-the-loop interface integrated with a layered **CIE** (Cognition–Interaction–Evolution) architecture, and session customization for modeling multi-lesson trajectories. In CIE, the cognition layer ensures individual consistency and instructional alignment, the interaction layer models priority-based authentic exchanges, and the evolution layer captures longitudinal changes in cognition, emotion and behavior. Together, these capabilities enable EduVerse to reproduce realistic classroom dynamics while supporting seamless human–agent interaction.

We instantiate EduVerse in middle school Chinese language classes—rich in open-ended discourse and emotional variation—and validate it through three CIE-aligned experiments: (i) Instructional alignment: simulated IRF rates (0.34–0.55) closely match real classrooms (0.37–0.49), indicating pedagogical realism. (ii) Group interaction: agent interaction networks reach a density of 0.27–0.40, approximating one-third of peer links and balancing individual variability with instructional stability. (iii) Cross-session evolution: positive transition rate R^+ improves by 11.7%, reflecting structured shifts in behavioral and cognitive engagement. (iv) Cross-disciplinary generalization: EduVerse adapts to history instruction while preserving IRF structures and peer dynamics, demonstrating robust transferability. Unlike conventional user-facing systems, the goal of EduVerse is to develop a foundational infrastructure for systematic educational simulations, shifting the evaluation focus from end-user experience to agent-level transparency and longitudinal interpretability. In sum, EduVerse captures individual- and group-level dynamics and reveals multi-dimensional learning trajectories across subjects and timescales.

Contributions. (1) We propose EduVerse, one of the first user-defined multi-agent classroom simulator, enabling reusable and customizable experimentation across tasks and disciplines. (2) We design the CIE architecture, which systematically models the cognitive, interactive, and evolutionary dynamics of developmental agents. (3) Through instantiated experiments, we demonstrate EduVerse’s effectiveness in authentic educational contexts. As an extensible open framework, EduVerse redefines virtual classroom modeling and establishes a systematic, cross-disciplinary pathway for educational AI; it will be open-sourced to encourage transparency and collaboration.

108 2 RELATED WORK

110 **EduVerse** provides a user-defined multi-agent simulation space that supports cognitive development,
 111 group interaction, and long-term evolution in virtual classrooms. Although educational agents,
 112 multi-agent simulations, and LLM-based generation have advanced, a unified platform integrating
 113 these dimensions is still missing. We therefore review three research threads aligned with EduVerse’s
 114 core dimensions (see App. B).

115 **Educational agents and virtual classrooms.** Early systems such as *Cognitive Tutor* (Anderson
 116 et al., 1995) and *SimStudent* (Matsuda et al., 2013) focused on skill acquisition and personalization,
 117 typically via rule- or model-based mechanisms (Christensen et al., 2011; Foley & McAllister, 2005;
 118 Carrington et al., 2011; Dotger et al., 2010). Teacher-training simulations used scripted virtual
 119 students as scaffolds but lacked adaptivity to feedback, peer influence, or classroom context (Kervin
 120 et al., 2006; Dieker et al., 2015; Delamarre et al., 2021; Shernoff et al., 2018; Özge Kelleci & Aksoy,
 121 2021). Recent generative extensions enable task-level learning (Zhang et al., 2024a; Lee et al., 2023;
 122 Yue et al., 2025; Mollick et al., 2024; Markel et al., 2023b; Wang et al., 2025b; Fahid et al., 2024),
 123 but often omit emotional modeling, stylistic progression, and multi-agent coupling, limiting their
 124 suitability for open, dynamic classrooms.

125 **Multi-agent social simulations.** Works such as *Generative Agents* show that LLMs enhanced with
 126 memory, planning, and reflection can generate human-like social behaviors in sandbox settings
 127 (Xu et al., 2025; Arana et al., 2025; Park et al., 2023; Li et al., 2023; Chen et al., 2023a; Jinxin
 128 et al., 2023b). However, these focus on adult roles and informal contexts, overlooking classroom-
 129 specific structures such as IRF discourse, teacher–student roles, and goal alignment. They also lack
 130 mechanisms for knowledge progression tracking and temporal adaptivity.

131 **Personalized modeling and long-term coherence.** Persona conditioning and style control are widely
 132 used to maintain role consistency (Shao et al., 2023; Jiang et al., 2024; Wang et al., 2024d), with
 133 design patterns surveyed by Tseng et al. (2024). Yet long-term interactions often suffer from persona
 134 drift, leading to memory-based prompting (Zhong et al., 2023), style constraints (Roy et al., 2023),
 135 and metacognitive or reflective mechanisms (Madaan et al., 2023; Li et al., 2025b; Didolkar et al.,
 136 2024). Research on continual and lifelong learning also contributes to longitudinal coherence (Wang
 137 et al., 2024c; Parisi et al., 2019; Zheng et al., 2024; Chen & Liu, 2018; Zheng et al., 2025; Maharana
 138 et al., 2024; Wang et al., 2025a; Tan et al., 2025; Li et al., 2025a). However, these methods are
 139 mostly evaluated in single-agent or non-classroom contexts, rarely integrating group-level structures
 140 or pedagogically grounded evolution. *EduAgent* (Xu et al., 2024) models individual cognitive and
 141 metacognitive processes but lacks multi-agent coordination and group dynamics.

142 Prior work provides important components—feedback, generative behaviors, and role consistency—but remains fragmented across time scales, modeling levels, and educational contexts. **Edu-
 143 Verse** unifies these dimensions by integrating user-defined environments, agents, and multi-session
 144 settings within the **CIE** architecture, yielding a scalable and interpretable platform that coherently
 145 models individual behavior, group dynamics, and cross-session evolution.

147 3 EDUVERSE FRAMEWORK

150 **EduVerse** is a user-defined multi-
 151 agent simulation framework for edu-
 152 cational settings, built to model the
 153 long-term cognitive, behavioral, and
 154 social dynamics of developing learners.
 155 It comprises three components:
 156 (i) a **user-defined environment** that
 157 configures layouts, seating, and inter-
 158 action networks to support diverse in-
 159 structional scenarios within a unified
 160 physical–social space (Sec. 3.1); (ii) **CIE-based agent modeling**, where student agents adopt a
 161 unified perception–cognition–action architecture with personalized embeddings and style modulation
 for cognitive coherence and expressive diversity, complemented by a human-in-the-loop interface for
 user customization (Sec. 3.2); and (iii) **interaction and evolution experiments** that integrate teacher-



162 **Figure 2: Visualization of student group interactions**
 163 **across classroom environments.** The three panels corre-
 164 spond to: Lecture (left, traditional teacher-centered layout),
 165 Collab_Two_Tables (middle, two-group collaborative setting),
 166 and Round_Table (right, open discussion layout).

162 led guidance with student-initiated behavior to assess instructional alignment, group interaction, and
 163 cross-session evolution (Sec. 3.3). Together (Fig. 1), these components offer a scalable, interpretable,
 164 and transferable foundation for systematic educational analysis.

166 3.1 USER-DEFINED ENVIRONMENT

168 The environment module constructs an interaction space that integrates *physical constraints* with
 169 *social semantics*. We adopt a hierarchical spatial structure $\mathcal{Z} = \{\mathcal{Z}_S, \mathcal{Z}_A, \mathcal{Z}_O, \mathcal{Z}_I\}$: \mathcal{Z}_S denotes
 170 functional *sectors* (e.g., teacher, student, activity zones), \mathcal{Z}_A denotes localized *arenas* (e.g., a
 171 discussion circle or a podium), \mathcal{Z}_O denotes interactive *objects* (e.g., blackboards, podiums, desks),
 172 and \mathcal{Z}_I represents fine-grained *items* (e.g., textbooks, pens, chalk). This layered organization provides
 173 a unified mapping between physical distribution and pedagogical semantics, consistent with App. C.1.

174 Peer interaction is captured by a seat-adjacency graph $A^{seat} \in \{0, 1\}^{N \times N}$ defined as

$$176 A_{ij}^{seat} = \begin{cases} 1, & \text{if students } i \text{ and } j \text{ satisfy the adjacency rules,} \\ 177 0, & \text{otherwise,} \end{cases} \quad (1)$$

178 where the rules may combine distance $d(i, j)$, group membership $g(i)$, and layout-specific constraints.
 179 Researchers can instantiate different interaction topologies by editing configuration files, avoiding
 180 hard-coded seat links.

182 As shown in Fig. 2, under this unified definition, EduVerse implements three canonical classroom
 183 layouts: **Lecture** constrains peer links by distance and group, reflecting teacher-centered, largely
 184 unidirectional communication; **Round_Table** augments distance-based adjacency with face-to-face
 185 *opposite-seat* edges $j = \text{opp}(i)$ to encourage open peer dialogue; **Collab_Two_Tables** forms fully
 186 connected within-group subgraphs with no cross-group links, emphasizing intra-group collaboration
 187 and bounded social structure.

188 These layouts serve as illustrative cases rather than limitations. Users can freely customize the
 189 hierarchy \mathcal{Z} and the adjacency-generation rules via configuration files to simulate classrooms of
 190 varying scales, tasks, and pedagogical styles. Leveraging the `seat_graph` mechanism, EduVerse
 191 tightly couples physical space with social semantics, providing a *realistic, controllable, and extensible*
 192 environment foundation for subsequent agent decision-making and group-level experiments.

193 3.2 CIE-BASED AGENT MODELING

195 Agent modeling in CIE maps directly onto three layers: the Cognition layer models individual
 196 differences through the Plan–Monitor–Regulate (PMR) loop; the Interaction layer captures role-
 197 differentiated social behavior via extended IRF mechanisms; and the Evolution layer models cross-
 198 lesson adaptation through memory and phase updates. Together, these layers integrate individual,
 199 social, and temporal dynamics into a unified framework (see App. C.2–C.5).

202 3.2.1 COGNITION ENGINE: COGNITION-DRIVEN AGENT DECISION MECHANISM

204 All agents \mathcal{A}_i follow the PCA architecture, formalized as:

$$205 \mathcal{A}_i^t : (\mathcal{O}_i^t, \mathbf{e}_i) \rightarrow a_i^t, \quad (2)$$

207 where \mathcal{O}_i^t is the local observation extracted from the global state \mathcal{S}^t via a perception function \mathcal{P}_i , and
 208 $\mathbf{e}_i = [\mathbf{p}_i; \mathbf{c}_i; \mathbf{m}_i]$ encodes personality traits, cognitive style, and motivation. The action is generated
 209 by a language model $a_i^t = f_{LLM}(\mathcal{O}_i^t, \mathbf{e}_i)$.

210 We adopt a lightweight interaction gate to decide whether an agent takes a turn at time t :

$$212 \mathcal{G}_i^t = \begin{cases} 1, & \text{if the scheduler assigns a teacher- or peer-directed turn to agent } i \text{ at time } t, \\ 213 0, & \text{otherwise (self-initiated behaviors may be scheduled separately).} \end{cases} \quad (3)$$

215 The cognitive loop consists of *Plan–Monitor–Regulate (PMR)*; the gate \mathcal{G}_i^t determines whether the
 loop is executed at time t .

Content–style separation. To balance long-term consistency with expressive diversity, we decouple semantic planning from stylistic expression. Inspired by style transfer (Gatys et al., 2016; Deng et al., 2022), we adopt a two-component design: (1) a *style modulator* fine-tuned on educational data with InternVL (Chen et al., 2024b) that produces style-aware prompts conditioned on traits and task phase (e.g., hesitancy, verbosity, affective tone), rather than direct responses (see details in App. C.2.3); and (2) a *cognitive generator* that integrates the style prompt with \mathcal{O}_i^t , \mathbf{e}_i , and dialogue history to form a composite prompt for GPT-4 (Achiam et al., 2023), which focuses on semantic planning and content generation. This design improves **cognitive coherence** and **expressive diversity**, while offering an interpretable path for personality-conditioned behaviors.

Role-specific parameterization. While student agents \mathcal{A}_S^i and the teacher agent \mathcal{A}_T share the PCA backbone, they differ in input channels, gating, and prompting. As shown in Tab. A4, students are modulated by personality and willingness embeddings, whereas the teacher relies on scripted lesson plans and classroom metrics. This unified yet differentiated design supports dynamics from teacher-led instruction to student-initiated contributions.

3.2.2 INTERACTION CORE: GROUP INTERACTION AND BEHAVIORAL COORDINATION

To better capture classroom discourse, CIE extends the classic IRF (Initiation–Response–Feedback) cycle to $I_T^t \rightarrow R_S^t \rightarrow F_T^t \rightarrow \text{Regulate}_S^t$. At time t , the teacher agent \mathcal{A}_T initiates a task T^t ; student agents \mathcal{A}_S^i respond, receive feedback, and then regulate subsequent actions, forming a micro-cycle aligned with instructional goals. Action selection follows Eq. 2 and is modulated by the interaction gate \mathcal{G}_i^t (see Eq. 3) to determine participation.

Intention function. We conceptualize willingness and responsiveness as $\omega_i^t = \alpha_1 P_i + \alpha_2 C_i^t + \alpha_3 R_i^t + \alpha_4 H_i^t + \alpha_5 S_{ij}^t$, where P_i denotes personality, C_i^t confidence at time t , R_i^t task relevance, H_i^t interaction history, and S_{ij}^t alignment with peer j ; α_k are weighting coefficients. In practice, this abstraction is embedded into prompt design and scheduling to guide gating and response generation. Beyond teacher-led turns, students may self-initiate behaviors (e.g., questioning, head-up), enabling multi-party interaction and group discussion. The teacher monitors these dynamics and provides targeted or global feedback, closing the loop between pedagogical intent, social context, and adaptive regulation for analyzing group coordination and evolution.

3.2.3 EVOLUTION LAYER: CROSS-LESSON ADAPTATION AND EVOLUTION

CIE supports long-term, cross-lesson simulation through four mechanisms: knowledge progression, behavioral style regulation, instructional pacing control, and memory interaction flow.

Knowledge progression. Each student agent \mathcal{A}_S^i initializes a knowledge state \mathbf{s}_i^0 derived from \mathbf{e}_i , which evolves as $\mathbf{s}_i^{t+1} = \mathcal{R}_i(\mathbf{s}_i^t, a_i^t, F_i^t)$, $\{\mathbf{s}_i^t\}_{t=1}^T$, where \mathcal{R}_i adjusts state components (e.g., confidence, engagement) using annotated behavioral signals (e.g., Bloom level, response type) and structured feedback (positive, neutral, negative).

Behavioral style regulation. At each step, actions, reflections, affect, and cognitive states are logged in a structured growth log (JSON), enabling the tracking of style stability, engagement shifts, and recovery. These logs also feed subsequent scheduling and adaptation.

Instructional pacing. The teacher agent organizes instruction into *phases*, each comprising multiple *steps*. After each phase, pacing is updated as $\text{Phase}_{k+1} \leftarrow \text{Transition}(\text{Phase}_k, \{\mathbf{s}_i^t\}, \text{completion rate})$, with policy π_T dynamically adjusting step granularity, tone, and targeting. In practice, cycles are initialized with 30 steps and then adapt to interaction dynamics, forming a closed loop for adaptive teaching control.

Memory interaction flow. To sustain cross-session continuity, CIE coordinates short- and long-term memory: long-term summaries are loaded at lesson start, short-term states are updated in real time, and aggregated records are written back after each session. This flow enables feedback-driven self-regulation and coherent developmental trajectories across lessons.

Taken together, the PCA backbone of CIE, coupled with mechanisms for cognition-driven decision-making, group interaction, and temporal evolution, yields behaviors that are *stable yet diverse* within

270 a lesson and *coherent* across lessons, providing a robust foundation for subsequent experiments and
 271 pedagogical analyses.

272 **3.3 INTERACTION AND EVOLUTION EXPERIMENTS**

274 This subsection formalizes EduVerse’s experimental paradigm, enabling researchers to configure
 275 environments, agents, and multi-session tasks to study cognitive alignment, group interaction, and
 276 longitudinal development across subjects. Users can specify physical–social environment, agent
 277 personas, instructional scripts and so on. On this basis, **four** experiments can be defined: (i) Cognition-
 278 driven instructional alignment experiments; (ii) Group interaction analysis and role differentiation
 279 experiments; (iii) Cross-session evolution and long-term development experiments; **(iv) Cross-
 280 disciplinary generalization experiments.** All experiments are logged and evaluated with unified
 281 metrics (e.g., IRF discourse structure, network density/centrality, positive transition rate R^+), ensuring
 282 interpretability and reproducibility. In addition, EduVerse provides a *human-in-the-loop* interface that
 283 admits real students or teachers alongside virtual agents (**all agent names are randomly generated and
 284 contain no identifiable or referential information**), enabling simulation, causal testing, and validation
 285 within a single, low-cost, controllable, and interpretable framework. In Sec. 4, we demonstrate these
 286 capabilities in a **junior secondary classroom**, highlighting EduVerse’s applicability and research
 287 value.

288 **4 EXPERIMENTAL DESIGN AND EVALUATION**

290 To demonstrate EduVerse’s customizability and cross-context transferability, we conduct four experiments
 291 across junior-secondary Chinese lessons and an additional Renaissance history lesson, covering
 292 cognitive alignment, group interaction, long-term development, and cross-disciplinary generalization.
 293 This setup enables evaluation under distinct discourse styles and instructional structures. Full implementation
 294 details are provided in App. D. The four experiments align with EduVerse’s core capacities:
 295 (1) **Experiment I** (Sec. 4.1): evaluates classroom authenticity and personality-conditioned alignment
 296 under customized environment settings; (2) **Experiment II** (Sec. 4.2): investigates group interaction and
 297 individual influence, and validates human–agent interaction through the open interface; (3)
 298 **Experiment III** (Sec. 4.3): tracks students’ behavioral, emotional, and cognitive trajectories across
 299 four consecutive lessons to illustrate cross-session evolution; (4) **Experiment IV** (Sec. 4.4): tests
 300 whether EduVerse generalizes to new cultural contexts, narrative instructional styles, and knowledge
 301 structures beyond Chinese language arts.

302 **4.1 EXPERIMENT I: ENVIRONMENT CUSTOMIZATION FOR COGNITION-DRIVEN**
 303 **INSTRUCTIONAL ALIGNMENT**

304 **Experiment I** tests whether customized environments can reproduce realistic classroom dynamics while
 305 retaining personality-driven behaviors described in Sec. 3.2. We instantiate three user-defined environments (Sec. 3.1) under a teacher-led mode and run ablations to assess key module contributions.

311 **IRF discourse patterns.** To assess whether EduVerse reproduces the structural logic of
 312 teacher–student dialogue rather than exact numerical matching, we compute the IRF rate as
 313
$$\text{IRF}_{\text{rate}} = \frac{1}{T} \sum_{t=1}^T \mathbf{1}(I_T^t = 1 \wedge R_S^t = 1 \wedge F_T^t = 1),$$
 where I_T^t , R_S^t , and F_T^t indicate the occurrence of teacher initiation, student response, and teacher
 314 feedback. Real classroom IRF data are sourced from the national Smart Education Platform and annotated
 315 through a standardized expert-reviewed protocol (App. D.3.2). As shown in Tab. 1, simulated
 316 IRF rates (0.336–0.554) lie within the structural range of real classrooms (0.367–0.486). Although
 317 numerical variation emerges across teachers, genres, and discourse styles, the consistent presence of
 318 complete IRF cycles indicates that EduVerse captures the underlying interaction structure shaping
 319 classroom discourse. A qualitative comparison (Tab. A8) further shows alignment in the I and R
 320 stages, with similar questioning and response patterns. Divergence mainly appears in the F stage:
 321 real teachers provide more open-ended or affective feedback, whereas simulated teachers respond
 322

323 Table 1: Average IRF distributions in simulated environments (**Sim**) vs. real classrooms (**Real**) across
 324 three text genres.

Genre	Setting	I	R	F	IRF _{rate}
<i>Lyrical Prose</i>	Sim	0.454	0.166	0.293	0.336
	Real	0.513	–	0.703	0.486
<i>Argumentative</i>	Sim	0.482	0.207	0.335	0.554
	Real	0.417	–	0.583	0.417
<i>Essay</i>	Sim	0.310	0.230	0.407	0.379
	Real	0.367	–	0.515	0.367
<i>Foreign Fiction</i>	Sim	0.310	0.230	0.407	0.379
	Real	0.367	–	0.515	0.367

more concisely. These differences reflect natural variation in teaching styles and do not affect the overall IRF structural consistency (App. D.3).

BEC (Behavior-Emotion-Cognition) across environments. To quantify students' BEC tendencies, we compute the normalized frequency of each category (App. D.2.3) over the class: $\text{BEC}(c) = \frac{1}{T} \sum_{t=1}^T \mathbf{1}(x_t = c)$, where x_t denotes the BEC label at timestep t and T is the total number of timesteps. This metric captures the *distribution of learner states*, rather than correctness, and is applied consistently across all comparisons in this subsection. Fig. 3 shows clear environment-dependent patterns: collaborative layouts yield the most positive emotion (0.547) and higher-order cognition (0.261); round-table layouts show more disengagement (0.254) and lower interaction (0.357); and lecture layouts reflect traditional classrooms with dominant lower-order cognition (0.819). EduVerse effectively reproduces environment-shaped classroom dynamics.

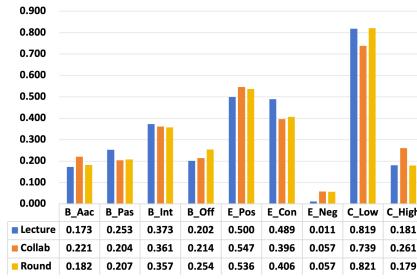


Figure 3: **Distribution of students' BEC across environments.** Collaborative layouts promote positivity and higher-order cognition, round-table increases disengagement, and lecture maintains passive, lower-order patterns.

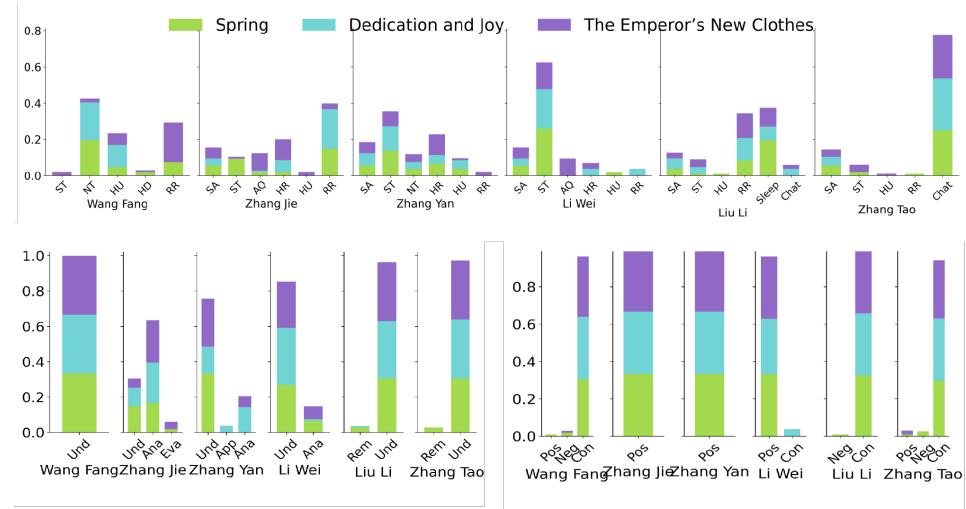


Figure 4: **Stable BEC patterns across genres within individual students.** Despite genre variation, individual BEC patterns remain stable and trait-consistent: highly extraverted students show active engagement and varied cognition, whereas low-openness or low-conscientiousness students tend toward disengagement, lower-order cognition, and confusion.

Personality-driven stability. As shown in Fig. 4, students maintain stable BEC distributions across genres, consistent with their traits: **Zhang Jie** (high extraversion) stays active and positive with varied cognition, whereas **Liu Li** (low openness) and **Zhang Tao** (low conscientiousness) show disengagement, lower-order cognition, and frequent confusion. These patterns demonstrate EduVerse's ability to preserve individual consistency and personality-conditioned behaviors.

Ablation study. Fig. 5 further validates the necessity of key modules. Removing the stylization module results (**framework_nolocal**) in evenly distributed emotions with amplified negativity, deviating from real classrooms where positive and confused states dominate. Removing the PMR module (**framework_nocog**) exaggerates higher-order cognition and active behaviors, resembling expert reasoning rather than gradual student development. Together, these results show that stylization ensures realistic emotional patterns, while the PMR module enforces educationally consistent cognitive

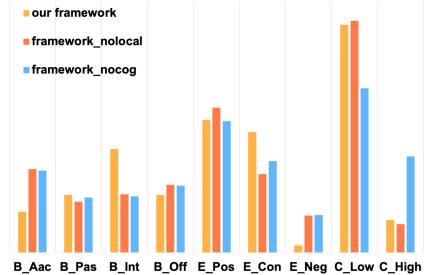


Figure 5: **Ablation study.** Removing the stylization module (**framework_nolocal**) increases negative emotions, while removing the PMR module (**framework_nocog**) inflates higher-order cognition and overly active behaviors.

378 and behavioral decisions, and their integration is indispensable for reproducing authentic classroom
 379 dynamics.
 380

381 **Summary.** Experiment I demonstrates that EduVerse reproduces authentic discourse, captures
 382 environment effects, preserves personality stability, and validates key modules, providing a solid
 383 basis for studying classroom design and instructional modes.

384 4.2 EXPERIMENT II: AGENT CUSTOMIZATION FOR GROUP INTERACTION ANALYSIS AND 385 ROLE DIFFERENTIATION

387 This experiment evaluates EduVerse’s ability
 388 to model interaction described in Sec. 3.2,
 389 moving from group-level networks to in-
 390 dividual influence, and finally testing hu-
 391 man–agent integration via the open interface.

392 **Group Interaction Analysis.** We model
 393 classroom interactions as undirected graphs,
 394 using density ($D = \frac{2E}{N(N-1)}$) and average
 395 degree ($k = \frac{2E}{N}$). As shown in Tab. 2, den-
 396 sity (0.267–0.400) and degree (1.2–1.667)
 397 indicate that 27–40% of ties are realized, re-
 398 reflecting realistic yet localized participation in
 399 teacher-led classrooms. Genre–environment
 400 effects also appear: argumentative essays and
 401 prose show lower density in Lectures, while
 402 fiction remains around 0.3 across settings, underscoring the narrative appeal of storytelling. Overall,
 403 genre and layout jointly shape engagement.

404 **Individual Influence Analysis.** We computed
 405 four directed metrics: *in-degree* (attention), *out-
 406 degree* (initiative), *degree centrality* (activity),
 407 and *betweenness* (bridging). As shown in Tab. 3,
 408 *Dedication and Joy* reveals mode-dependent
 409 roles. In the Lecture, **Zhang Jie** had a high in-
 410 degree but no initiative, while **Zhang Tao** and
 411 **Zhang Yan** showed the opposite. In Collab,
 412 reciprocity increased, with **Zhang Tao** emerg-
 413 ing as a connector and **Zhang Jie** shifting to
 414 side-talk. In Round, roles were decentralized,
 415 yet **Zhang Tao** became most central (highest
 416 out-degree, degree, and betweenness), whereas
 417 **Liu Li** was marginalized. (see Fig. 2 for the
 418 visualization of student interactions). These results illustrate how classroom organization reshapes
 419 roles, moving individuals from peripheral to core positions.

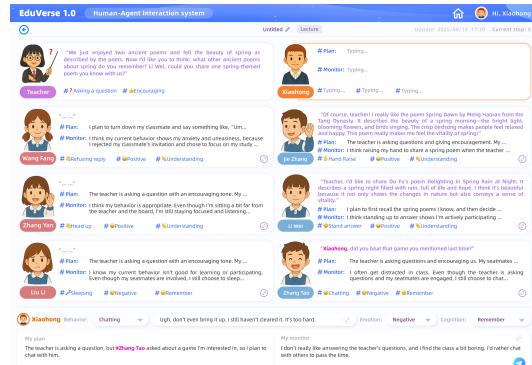
420 Table 3: Distribution of students’ network centrality indicators in *Dedication and Joy* across environ-
 421 ments. Values are normalized to [0, 1]. **Deg.** = degree centrality; **Betw.** = betweenness centrality.

422 Student	423 Lecture				424 Collab				425 Round			
	426 In	427 Out	428 Deg.	429 Betw.	430 In	431 Out	432 Deg.	433 Betw.	434 In	435 Out	436 Deg.	437 Betw.
438 Li Wei	0.25	0.25	0.50	0	0.25	0.25	0.50	0	0.20	0.20	0.40	0
439 Liu Li	0.25	0.25	0.50	0	0.25	0.25	0.50	0	0.00	0.20	0.20	0
440 Zhang Tao	0.00	0.25	0.25	0	0.50	0.25	0.75	0.083	0.20	0.60	0.80	0.15
441 Zhang Jie	0.50	0.00	0.50	0	0.25	0.25	0.50	0	0.40	0.20	0.60	0.10
442 Zhang Yan	0.00	0.25	0.25	0	0.25	0.50	0.75	0.083	0.20	0.20	0.40	0
443 Wang Fang	–	–	–	–	–	–	–	–	0.40	0.00	0.40	0

444 **Human–Agent Interaction.** To evaluate human–agent integration, we evaluate human–agent in-
 445 tegration through the EduVerse visual interface (Fig. 6), which enables ChatGPT-style interaction

384 Table 2: Group interaction analysis across lessons and
 385 environments. Values report nodes, edges, density,
 386 and average degree of the interaction graph. **Bold**
 387 marks the highest values per lesson.

Lesson	Env.	Nodes	Edges	Density	Avg. Deg.
388 <i>Foreign Fiction</i>	Lecture	6	5	0.333	1.667
	Collab	5	3	0.300	1.200
	Round	6	5	0.333	1.667
389 <i>Argumentative Essay</i>	Lecture	5	3	0.300	1.200
	Collab	5	4	0.400	1.600
	Round	6	5	0.333	1.667
390 <i>Lyrical Prose</i>	Lecture	6	4	0.267	1.333
	Collab	5	3	0.300	1.200
	Round	6	5	0.333	1.667



391 Figure 6: Human-Agent interaction interface.

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432 with student agents. Four interaction types, including peer chat, peer academic response, teacher
 433 Q&A, and teacher intervention, were tested within this interface (Fig. A3, App. D.4). Results aligned
 434 with personality traits: **Zhang Tao** (talkative) responded most (0.53–0.73) and initiated conversations
 435 in Collab/Round, while **Zhang Jie** (high-extraversion) responded less (0.27–0.40). Teacher agents
 436 succeeded in all Q&A and interventions, ensuring robust instructional control. These findings confirm
 437 EduVerse’s capacity for seamless human integration with role-driven realism.

438 **Summary.** EduVerse captures group patterns, individual traits, and human–agent integration, validating
 439 its ability to model authentic and adaptive classroom interactions.

442 4.3 EXPERIMENT III: SESSION CUSTOMIZATION FOR CROSS-SESSION EVOLUTION AND 443 LONG-TERM DEVELOPMENT

445 Experiment III tests whether virtual students show pro-
 446 gressive development described in Sec. 3.2 by mapping
 447 BEC states to ordered levels and treating upward transi-
 448 tions as positive shifts. Across four sessions (*Spring I-II*,
 449 *Dedication and Joy I-II*), we assess long-term engagement
 450 and learning trajectories.

451 **Session-level Evolution.** We quantify progression us-
 452 ing the positive-transition rate. For a state sequence
 453 $\{s_t\}$ with priority $P(s_t)$, a transition is positive when
 454 $P(s_{t+1}) > P(s_t)$. Let $T^+ = \sum_t \mathbf{1}[P(s_{t+1}) > P(s_t)]$,
 455 $R^+ = T^+/T$. As shown in Fig. 7, behavior improves
 456 rapidly across sessions, emotion rises early and stabilizes,
 457 and cognition grows more slowly, reflecting its need for
 458 sustained accumulation. These patterns indicate that Edu-
 459 Verse captures realistic dynamics where behavior and af-
 460 fect shift quickly, while cognitive development progresses gradually.

461 **Individual-level Evolution.** As shown
 462 in Fig. 8 and Tab. A13, students ex-
 463 hibit clear divergence across four ses-
 464 sions. **Wang Fang** improves steadily
 465 (0.057→0.205); **Zhang Jie** remains
 466 consistently strong (0.483–0.603) with
 467 ceiling-level emotion ($E_{Pos} = 1.000$);
 468 **Zhang Yan** accelerates late, reaching
 469 0.923 in behavior; **Li Wei** maintains high
 470 emotion ($E_{Pos} \geq 0.966$) but shows
 471 limited cognitive gains; **Liu Li** pro-
 472 gresses gradually overall (0.011→0.179);
 473 and **Zhang Tao** fluctuates markedly
 474 (0.080–0.256). These trends show Edu-
 475 Verse’s ability to capture differentiated
 476 and realistic learner trajectories.

477 **Ablation on the Regulate Module.** To evaluate the role of
 478 BEC regulation, we remove the Regulate stage and compare
 479 cross-session positive transitions. As shown in Tab. 4, overall
 480 gains drop from 0.117 to 0.098, driven by declines in behavior
 481 (+7.0%) and emotion (+5.1%). The larger cognitive gain with-
 482 out regulation reflects unstable high-level jumps, mirroring the
 483 PMR ablation in Experiment I, rather than genuine progress. With regulation enabled, transitions
 484 become more stable and educationally plausible, confirming its importance for realistic long-horizon
 485 learning.

486 **Summary.** EduVerse captures long-term learning evolution: behavior and emotion improve quickly,
 487 while cognition develops more slowly, reflecting realistic developmental variation.

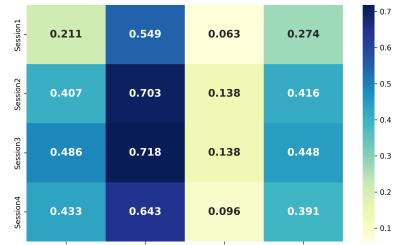


Figure 7: **Positive transition trends in cross-session evolution.** Rates of positive shifts in BCE increase over time, with behavior improving most rapidly, emotion rising steadily, and cognition progressing gradually.

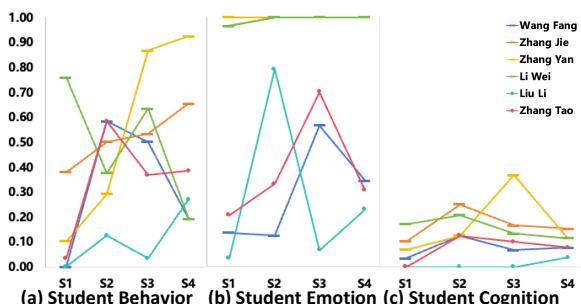


Figure 8: **Individual trajectories of positive shifts across sessions.** Students display differentiated developmental paths in behavior, emotion, and cognition, closely aligned with personality traits, validating EduVerse’s capacity to model personalized learning evolution.

Table 4: **Ablation on the Regulate.**

Variant	ΔB_{Pos}	ΔE_{Pos}	ΔC_{Pos}	ΔAll
w/o R	0.152	0.043	0.098	0.098
Full	0.222	0.094	0.033	0.117

With regulation enabled, transitions become more stable and educationally plausible, confirming its importance for realistic long-horizon learning.

486 4.4 EXPERIMENT IV: CROSS-DISCIPLINARY GENERALIZATION TO HISTORY LESSON
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488 To assess cross-disciplinary adaptability, we add a
489 Renaissance history lesson, distinct from Chinese in
490 cultural background and teaching style, while keeping
491 all agent settings fixed, testing whether EduVerse
492 adapts without additional tuning.

493 **IRF discourse structure.** Real classrooms show
494 clear subject differences (Tab. 5): Chinese exhibits
495 denser IRF patterns (0.423), whereas history is more
496 explanatory and therefore sparser (0.333). EduVerse
497 reproduces this divergence, yielding 0.423 for Chi-
498 nese and 0.226 for history. This alignment with
499 real trends shows that EduVerse captures discipline-
500 specific interaction intensity while preserving the
501 core IRF structure, demonstrating robust cross-disciplinary transfer.

502 **Group interaction Analysis.** As shown in Tab. 6, student
503 networks maintain substantial connectivity across layouts,
504 with densities ranging from 0.333 in round and collabora-
505 tive settings to 0.5 in the lecture layout—closely matching
506 interaction levels observed in Chinese lessons. Beyond
507 the numeric patterns, the visualized networks in Fig. 9 re-
508 veal clear topological distinctions: history lessons produce
509 shorter, localized chains, whereas literature lessons form
510 broader, discussion-oriented clusters.

511 **Summary.** These findings indicate that while disciplinary
512 context shapes the magnitude of IRF patterns, EduVerse
513 consistently generates coherent and adaptive interaction
514 dynamics and network topology across domains.

515 5 CONCLUSION
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517 We introduced EduVerse, a user-
518 defined multi-agent simulation
519 framework that unifies cognition,
520 interaction, and evolution to model
521 developmental student
522 agents. Trait-conditioned learn-
523 ers generated by EduVerse be-
524 have consistently yet adaptively
525 across instructional contexts.
526 Across four experiments, Edu-
527 Verse reproduces key classroom
528 phenomena: realistic IRF struc-
529 tures and personality-driven be-
530 haviors (Exp. I), coherent peer-
531 interaction patterns and smooth
532 human–agent integration (Exp.
533 II), and meaningful long-term
534 development with an 11.7% in-
535 crease in positive transitions (Exp. III). A Renaissance history lesson further demonstrates cross-
536 disciplinary generalization, with IRF density and interaction topology reorganizing in discipline-
537 consistent ways while core pedagogical structures remain stable (Exp. IV). Together, these results
538 show EduVerse as a scalable and transferable platform for modeling learning processes and supporting
539 research in adaptive learning, human-in-the-loop teaching, and cross-disciplinary educational AI.

Table 5: Comparison of simulated and real-
classroom IRF patterns across subjects. “H”
= History; “C” = Chinese; “Sim” = simulated
classrooms; “Real” = real classroom data.

Setting	Subjects	I	R	F	IRF _{rate}
Sim	H_lecture	0.205	0.269	0.385	0.282
	H_collab	0.256	0.226	0.415	0.282
	H_round	0.143	0.071	0.329	0.114
	H_avg	0.201	0.189	0.376	0.226
	C_avg	0.416	0.201	0.345	0.423
Real	H	0.359	—	0.513	0.333
	C	0.432	—	0.600	0.423

Table 6: Group interaction analysis for
the simulated history lesson. “Nodes”
denote student agents; “Edges” represent
realized peer interactions. Density and
average degree reflect interaction intensity
under Lecture, Collaborative, and
Round layouts.

Env.	Nodes	Edges	Density	Avg. Deg.
Lecture	4	3	0.500	1.500
Collab	6	5	0.333	1.667
Round	6	5	0.333	1.667

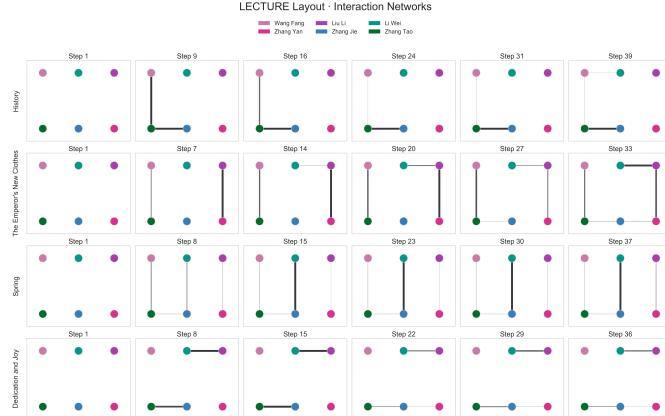


Figure 9: **Interaction network under the lecture layout for four subjects.** Nodes represent student agents and edges denote peer interactions. History lessons yield more localized exchanges, while literature lessons form broader discussion chains, reflecting disciplinary variation with stable core interaction patterns.

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ETHICS STATEMENT542
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This study adheres to established ethical standards for research involving educational data and
human–AI interaction. All real classroom materials used in this work, including video content
and instructional transcripts, were obtained exclusively from nationally released open educational
platforms. These resources are officially published by educational authorities, publicly accessible,
and contain no private or restricted information. The instructional transcripts used for analysis include
only teacher–student dialogue from publicly available lessons and do not contain identifiable student
images or personal data.549
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No new data involving minors were collected for this research. The study did not conduct experiments,
interviews, or interactions with students, nor did it gather additional information from schools,
teachers, or learners. Aside from publicly released classroom transcripts, all classroom dialogues,
behavioral annotations, and emotion labels were generated by large language models and do not
contain any real personal information.554
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Human–agent interaction experiments in this work were limited to internal system functionality and
robustness testing. All interactions were performed solely by members of the research team, with
no recording, storage, or analysis of personal information. The purpose of these interactions was to
validate the technical performance of the system rather than to study human subjects. As such, these
activities do not constitute human-subject research.559
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All data used in this study have been anonymized and are employed strictly for academic research.
Raw transcripts from public educational platforms are not released or reproduced within the paper.
No data are used for commercial purposes. The research design follows principles of transparency,
privacy protection, and minimal risk.564
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REPRODUCIBILITY STATEMENT566
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To support reproducibility, we will release the EduVerse codebase, environment settings, preprocessing
scripts, and trained models. Processed resources and evaluation protocols will also be provided.
All resources will be made available upon acceptance.570
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1080	APPENDIX	
1081		
1082	APPENDIX CONTENTS	
1083		
1084		
1085	A The Use of Large Language Models (LLMs)	22
1086		
1087	B Comprehensive Related Works	22
1088	B.1 Educational Agents and Virtual Student Simulations	22
1089	B.2 LLM-driven Multi-agent Social Simulations	22
1090	B.3 Personalized Modeling and Behavioral Consistency Mechanisms	23
1091		
1092		
1093	C Detailed Information for EduVerse Framework	26
1094		
1095	C.1 Detailed Description of Environment Module	26
1096	C.2 Detailed Description of Cognition Engine	28
1097	C.3 Detailed Description of Social Situatedness	36
1098	C.4 Detailed Description of Temporal Dynamics	38
1099		
1100	C.5 Memory Mechanisms for Agent Cognition	40
1101		
1102		
1103	D Detailed Information for Experimental Design and Evaluation	43
1104	D.1 Experiment Setup and Configuration	43
1105	D.2 BEC Generated Framework	45
1106		
1107	D.3 Experiment I	47
1108		
1109	D.4 Experiment II	51
1110		
1111	D.5 Experiment III	54
1112		
1113	D.6 Experiment IV	56
1114		
1115	E Multi-Agent Instructional Interaction Cases across Genre-Specific Tasks	61
1116		
1117		
1118		
1119		
1120		
1121		
1122		
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1124		
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1134 **A THE USE OF LARGE LANGUAGE MODELS (LLMs)**
11351136 During manuscript preparation, Large Language Models (LLMs) were employed solely for language
1137 refinement and stylistic polishing.
11381139 **B COMPREHENSIVE RELATED WORKS**
11401141 **B.1 EDUCATIONAL AGENTS AND VIRTUAL STUDENT SIMULATIONS**
11421143 Modeling virtual student agents has long been a central thread in educational AI research (Dai &
1144 Ke, 2022; Chou et al., 2003; Chheang et al., 2024). As early as the 1990s, researchers introduced
1145 “teachable agents” to support teacher training and foster learning by teaching. Representative
1146 examples include VanLehn et al.’s work in physics tutoring (VanLehn et al., 1994) and the Betty’s
1147 Brain system (Biswas et al., 2005), which formalized the learning-by-teaching paradigm. However,
1148 these systems relied heavily on scripted behavioral policies and static knowledge-update mechanisms,
1149 limiting their ability to capture temporal dynamics in student behavior and affect. Similarly, traditional
1150 intelligent tutoring systems emphasized knowledge mastery (e.g., skill tracing) but paid little attention
1151 to developmental trajectories.
11521153 The advent of large language models (LLMs) has enabled a new generation of educational agents,
1154 characterized by open-ended interaction, behavioral diversity, and learner-like imperfections (Russin
1155 et al., 2024; Chu et al., 2025; Moore et al., 2023). Recent work has leveraged prompt-conditioned
1156 LLMs to simulate students with varying ability levels, personalities, and misconceptions (Wang et al.,
1157 2024a; Glaese et al., 2022). For example, Lu and Wang (Lu & Wang, 2024) proposed the Generative
1158 Students framework to assess item difficulty through simulated learners; Markel et al. (Markel
1159 et al., 2023a) introduced GPTeach to enhance teacher training with diverse LLM-generated student
1160 responses; and Jin et al. (Jin et al., 2025a) developed TeachTune, which evaluates instructional
1161 agents against a spectrum of student personas, highlighting how pedagogical strategies adapt to
1162 personality-driven differences.
11631164 Beyond individual interactions, researchers have explored classroom-level simulations with multi-
1165 agent LLM frameworks. AgentVerse (Chen et al., 2023b) and CGMI (Jinxin et al., 2023a) enable
1166 heterogeneous agents to engage in collaborative and instructional roles. Building on this, Sim-
1167 Class (Zhang et al., 2024b) incorporates a class manager to coordinate Initiation–Response–Feedback
1168 (IRF) dialogues between teacher and student agents, achieving high realism: agents respond to
1169 teacher prompts, initiate follow-ups, maintain turn-taking, and even exhibit emergent behaviors such
1170 as spontaneous group discussions and peer-led task completion. These advances mark an important
1171 step from scripted interactions toward socially grounded, self-organizing classroom learning.
11721173 Nevertheless, existing systems remain limited in modeling long-term behavioral evolution, affective
1174 regulation, and stylistic coherence, with most constrained to single-session interactions. In contrast,
1175 **EduVerse** provides a unified, multi-level simulation platform that supports user-defined modeling
1176 of physical environments, agent configurations, and cross-session evolution. Its open interfaces
1177 allow researchers to flexibly configure classroom layouts, seating arrangements, and interaction
1178 networks, and systematically examine learners’ cognitive development and group dynamics. Through
1179 this design, EduVerse bridges the gap between scripted tutor–learner simulations and scalable,
1180 development-oriented classroom modeling.
11811182 **B.2 LLM-DRIVEN MULTI-AGENT SOCIAL SIMULATIONS**
11831184 The rise of large language models has fueled a new wave of multi-agent simulations, where agents act
1185 as generative entities capable of open-ended dialogue and socially coherent behavior (Guo et al., 2024;
1186 Gao et al., 2024; Hua et al., 2023). A landmark example is *Generative Agents* by Park et al. (Park
1187 et al., 2023), which deployed 25 GPT-powered agents in a virtual town. Each agent followed a daily
1188 routine, formed human-like relationships, and even organized a collective event without external
1189 control, illustrating how memory and reflection mechanisms support emergent behaviors. This work
1190 sparked broad interest in agent-based modeling grounded in persistent memory and self-regulation.
11911192 Subsequent studies extended this paradigm to collaborative and adversarial settings. ChatDev (Qian
1193 et al., 2023) and MetaGPT (Hong et al., 2023) simulated professional teams by embedding role-
1194

1188 specific prompting and structured communication flows, thereby improving task-level coherence.
 1189 Wang et al. (Wang et al., 2023) showed that even single-agent simulations can emulate multi-agent
 1190 reasoning by activating multiple internal personas through self-dialogue, enhancing creativity and
 1191 logical reasoning.

1192 Competitive scenarios provide further evidence of emergent strategy. Xu et al. (Xu et al., 2023)
 1193 employed GPT agents in the game Werewolf to model deception, persuasion, and coalition dynamics.
 1194 In economics, Horton (Horton, 2023) and Aher et al. (Aher et al., 2023) embedded LLM agents in
 1195 negotiation and public goods games, demonstrating rational decision-making alongside human-like
 1196 biases. Together, these studies underscore the feasibility of LLM agents as proxies for large-scale
 1197 human social behavior.

1198 Nonetheless, these systems largely focus on adult interactions and informal contexts, lacking the
 1199 structured pedagogical mechanisms required for educational environments. Most do not support
 1200 teacher-student dialogue based on IRF cycles, nor do they capture learner development over time or
 1201 adapt to knowledge progression and group dynamics. In contrast, **EduVerse** introduces LLM-driven
 1202 multi-agent simulation into education, integrating structured classroom discourse (e.g., IRF cycles),
 1203 metacognitive regulation, and cross-session evolution. This provides a scalable and interpretable
 1204 platform for modeling instructional interactions and systematically examining the developmental
 1205 trajectories of learners.

1206

1207 B.3 PERSONALIZED MODELING AND BEHAVIORAL CONSISTENCY MECHANISMS

1208

1209 Maintaining long-term consistency of personality, language style, and behavioral patterns remains a
 1210 central challenge in LLM-driven multi-agent environments (Guo et al., 2024; Li et al., 2024b; Tran
 1211 et al., 2025). Despite their generative fluency, LLMs often suffer from “persona drift” in extended
 1212 interactions, where role-specific traits weaken or deviate over time (Xu et al., 2023). For example,
 1213 a student agent initially designed to be introverted may gradually adopt assertive conversational
 1214 patterns, undermining the credibility of long-term simulations. Such issues arise from limited identity
 1215 retention and emotional coherence, motivating research on role stabilization mechanisms.

1216

1217 Early dialogue systems attempted to preserve character identity through structured profiles and
 1218 task-specific memory modules. PersonaChat (Zhang et al., 2018), for instance, embedded fixed
 1219 persona facts, while later work introduced memory modules to retain role-consistent traits across
 1220 turns (Ouyang et al., 2022). These approaches proved effective in short sessions but struggled with
 1221 complexity and duration. In LLM-based agents, persona-conditioned prompting became a common
 1222 strategy, though it often failed under topic shifts or multi-phase tasks (Xu et al., 2023).

1223

1224 Recent advances emphasize fine-tuning and reward-based alignment to improve role fidelity (Ji
 1225 et al., 2025b; Chen et al., 2025). CharacterGLM (Zhou et al., 2023) and Ditto (Lu et al., 2024)
 1226 enhanced intra-role consistency by training on persona-labeled dialogues or generating synthetic
 1227 role-specific corpora. Reinforcement Learning from Human Feedback (RLHF) further penalized
 1228 off-character outputs, reinforcing behavioral alignment. However, these methods face scalability
 1229 challenges, including data costs and generalization trade-offs.

1230

1231 To mitigate reliance on supervised correction, self-monitoring strategies have emerged (Li et al.,
 1232 2025d; Behore et al., 2024). Ji et al. (Ji et al., 2025a) introduced a role-aware reflection loop that
 1233 allows models to detect and revise misaligned outputs. Coupled with contrastive training, this
 1234 approach significantly improved long-term role consistency. Memory-augmented designs provide
 1235 additional scaffolding: systems log key interactions and behavioral states, with summarization or
 1236 vector retrieval supporting continuity in future outputs (Park et al., 2023; Ouyang et al., 2022).

1237

1238 These developments are particularly salient in education. To simulate realistic learners, researchers
 1239 have designed student agents with distinct cognitive and non-cognitive traits. TeachTune (Jin et al.,
 1240 2025a) showed that teacher agents adjust feedback strategies depending on student profiles such as
 1241 confidence or anxiety, while Li et al. (Li et al., 2025c) modeled “imperfect learners” by injecting
 1242 errors into outputs, prompting teacher agents to practice remediation. Such findings highlight the
 1243 pedagogical utility of stable yet differentiated learner personas.

1244

1245 **EduVerse** advances this line of work by integrating profile-driven planning, memory-aligned reg-
 1246 ulation, and behavior-consistent generation into its Cognition–Interaction–Evolution framework.
 1247 Compared to single-agent approaches, EduVerse achieves both intra-agent coherence and inter-agent

1242 variation at the classroom scale, providing a scalable and interpretable solution for educational
1243 simulation.
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Table A1: Comparison of multi-agent educational simulation frameworks.

Framework	Environment Customization				Agent Customization				Interaction and Evolution Experiments			
	Environment Layouts	Physical Layouts	Seating	Theory-based Modeling	Cognition	Teacher-Student	Group	Human-Agent	Long-time Evolution	Real-vs-Simulated Comparison	Group-Level Analysis	Individual-Level Analysis
AgentSchool Jin et al. (2025b)	✓	✗	✗	✓	✓	✓	✗	✓	✓	✗	✓	✓
PEERS Arana et al. (2025)	✓	✗	✗	✓	✓	✓	✗	✗	✗	✗	✗	✓
Contextual Agents Xu et al. (2025)	✗	✗	✗	✓	✗	✗	✗	✓	✓	✓	✓	✓
Simulating Classroom Zhang et al. (2024a)	✗	✗	✗	✓	✓	✓	✓	✓	✗	✗	✓	✓
MathVC Yue et al. (2025)	✗	✗	✗	✓	✗	✓	✓	✓	✗	✗	✓	✓
AgentVerse Chen et al. (2023b)	✓	✗	✗	✗	✓	✓	✓	✓	✗	✗	—	—
GPTeach Markel et al. (2023b)	✗	✗	✗	✓	✗	✗	✓	✓	✗	✗	✗	✓
Generative Agent Lee et al. (2023)	✓	✗	✗	✓	✗	✗	✓	✓	✗	✗	✗	✓
EduVerse	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

1350 **C DETAILED INFORMATION FOR EDUVERSE FRAMEWORK**
13511352 **C.1 DETAILED DESCRIPTION OF ENVIRONMENT MODULE**
13531354 **C.1.1 HIERARCHICAL SPATIAL ORGANIZATION**
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1356 EduVerse models classroom environments using a four-tiered hierarchical spatial structure $\mathcal{Z} =$
 1357 $\{\mathcal{Z}_S, \mathcal{Z}_A, \mathcal{Z}_O, \mathcal{Z}_I\}$, corresponding to **Sector**, **Arena**, **Object**, and **Item**. This design supports
 1358 pedagogically meaningful interactions and dynamic behavior generation, and provides semantic
 1359 alignment between agent perception, spatial context, and task execution.

1360 At the top level, a **Sector** partitions the virtual classroom into functional instructional zones, e.g.,
 1361 *Teacher Sector*, *Student Sector*, and *Activity Sector*. Within each sector, an **Arena** specifies localized
 1362 interactive regions—such as a discussion circle or a teaching podium—that constrain mobility
 1363 and determine perceptual access to nearby objects. **Objects** embedded within Arenas (e.g., desks,
 1364 blackboards, presentation screens) serve as anchors for attention and instructional actions. **Items**
 1365 (e.g., chalk, textbooks, notebooks) are the most granular perceivable units and constitute the basic
 1366 elements of fine-grained interaction.

1367 For example, in the *Teacher Podium Arena*, a blackboard and lectern support behaviors such as
 1368 lecturing and board writing. In contrast, a *Student Group Arena* contains desks and personal learning
 1369 materials, enabling small-group collaboration or individualized learning. A complete layout instance
 1370 typically includes multiple sectors, each containing several arenas populated with pedagogically
 1371 structured objects and items (e.g., chalk, erasers, water cups), collectively forming a coherent four-
 1372 level spatial graph (see Tab. A2). This hierarchical structure supports classroom configurations
 1373 ranging from lecture-centric layouts to collaborative or round-table setups, and allows real-time
 1374 adaptation of spatial roles, interaction boundaries, and perception zones as classroom dynamics
 1375 evolve.

1376 **Table A2: Hierarchical Classroom Environment Structure**
1377

Sector (ID)	Arena	Object	Items
Teacher Zone (10001)	Resource Display Area	Blackboard	Chalk, Blackboard Eraser
Teacher Zone (10001)	Podium Area	Podium Desk	Cup, Textbook, Mobile Phone, Chalk
Teacher Zone (10001)	Instruction Area	Electronic Whiteboard	—
Student Zone (20001)	Group A Area	Student $A_{1\dots N}$	Textbook, Cup, Pencil Case, Pen, Backpack
Student Zone (20001)	Group B Area	Student $B_{1\dots N}$	—
Activity Zone (30001)	Storage Area	Cleaning Supplies	Broom, Mop
Activity Zone (30001)	Storage Area	Daily Utilities	Clock, Cabinet, Water Dispenser

1389 Note: This table instantiates the 4-level spatial structure in **EduVerse**—Sector, Arena, Object, and Item.
 1390 Each arena defines a functional subspace containing interactive objects for perception and behavior
 1391 planning.

1392 **C.1.2 INTERACTION AFFORDANCES AND CONSTRAINTS**
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1394 The spatial hierarchy also functions as an interaction scaffold that governs how agents perceive, move,
 1395 and act. Layouts map to pedagogical strategies: lecture-centric configurations emphasize teacher-led,
 1396 unidirectional communication, while round-table or collab-based layouts promote peer collaboration.
 1397 The “Sector–Arena–Object–Item” hierarchy accommodates these variations and enables dynamic
 1398 spatial adaptation during simulation.

1399 In the current implementation, spatial location primarily conditions behavioral availability. For
 1400 example, only students within a *Presentation Arena* can access teacher content in real time; in group
 1401 tasks, shared Arena–Object associations trigger peer-based interactions. EduVerse thus enforces mode-
 1402 specific constraints (lecture, presentation, group discussion), with corresponding action permissions.

Beyond this, the framework is designed to be extensible. For instance, each student can be assigned a personalized `perception_config` (e.g., perceptual radius and maximum trackable items), and collision constraints or spawn configurations can be integrated to enhance physical realism. While not activated in the current experiments, these extensions illustrate the scalability of EduVerse towards more fine-grained behavioral planning and environment fidelity.

C.1.3 SEAT_GRAPH FORMALIZATION AND LAYOUT TEMPLATES

We define the seat graph as an unweighted adjacency matrix $A^{\text{seat}} \in \{0, 1\}^{N \times N}$, where

$$A_{ij}^{\text{seat}} = \begin{cases} 1, & \text{if } i \text{ and } j \text{ satisfy the layout-specific adjacency rule,} \\ 0, & \text{otherwise.} \end{cases}$$

Formally, EduVerse provides three canonical layouts:

- Lecture Adjacency is primarily defined within rows, restricted to students sitting close to each other:

$$A_{ij}^{\text{seat}} = \mathbb{I}[d(i, j) \leq \tau_d \wedge \text{row}(i) = \text{row}(j)].$$

- Round Table Students are seated around circular tables; adjacency includes both immediate neighbors and face-to-face counterparts:

$$A_{ij}^{\text{seat}} = \mathbb{I}[j = \text{neighbor}(i) \vee j = \text{opp}(i)].$$

- Collab_Two Tables Within-group students are fully connected, while across-group edges are suppressed:

$$A_{ij}^{\text{seat}} = \mathbb{I}[g(i) = g(j)].$$

Thus, the seat graph provides a baseline, layout-dependent topological structure:

$$A^{\text{seat}} = \begin{cases} A_{\text{Lecture}}^{\text{seat}}, & \text{if layout = Lecture,} \\ A_{\text{Round}}^{\text{seat}}, & \text{if layout = Round Table,} \\ A_{\text{Collab}}^{\text{seat}}, & \text{if layout = Collab_Two_Tables.} \end{cases}$$

This structure is a binary, unweighted topology that captures only peer adjacency. It does not yet encode higher-order social or instructional factors. Instead, it serves as a foundation upon which *cognitive planning* can later be modeled by incorporating teacher and board visibility.

C.1.4 COGNITIVE PLANNING AND DISTANCE EFFECTS

The physical distances encoded in the seat graph directly affect students' cognitive planning. While the seat graph itself captures only peer proximity relations, the cognitive planning process requires a richer consideration of spatial constraints, including student–student, student–teacher, and student–board distances. Importantly, these spatial factors constitute only *one component* of cognitive planning; other psychological, pedagogical, and contextual variables also play a crucial role, but here we explicitly highlight the influence of the physical environment.

Distance-based cognitive factors

Let $p_i \in \mathbb{Z}^2$ denote the spatial position of student i . We define three forms of distance measures relevant to cognitive planning:

- **Peer distance:**

$$d(i, j) = \|p_i - p_j\|_2, \quad i \neq j,$$

capturing the Euclidean distance between students i and j .

- **Teacher distance:**

$$d_T(i) = \|p_i - p_T\|_2,$$

where p_T denotes the teacher's position. This distance reflects the cognitive accessibility of the teacher, which is essential for attention allocation and interaction.

1458 Table A3: Environment configuration parameters in EduVerse. Parameters specify spatial layout,
 1459 interaction rules, and perception constraints.

1460

1461 Parameter	1462 Description
1463 Grid size	1464 30×20 discrete lattice
1464 Layout type	1465 Lecture / Round Table / Collaborative (two tables)
1465 Table radius	1466 Default = 3 grid units
1466 Table gap	1467 Default = 10 grid units (between two tables)
1467 Objects	1468 Students, teacher, podium, board, tables
1468 Peer adjacency	1469 Edge (i, j) if $d(i, j) \leq \tau_d = 4.5$
1469 Group adjustment	1470 Threshold +1.0 if $g(i) = g(j)$
1470 Round Table rule	1471 Add cross-table “opposite” edges
1471 Collaborative rule	1472 Within-table complete graph; no inter-table edges
1472 Perception radius	$r = 8$ grid units
1473 Perception capacity	$\kappa = 5$ objects per student
1474 Collision/occupancy	1475 One object per grid cell; invalid moves rejected

1473

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• **Board distance:**

$$d_B(i) = \|p_i - p_B\|_2,$$

1476 where p_B denotes the board’s position. This measure captures the visibility and salience of
 1477 instructional materials.

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Integration into cognitive planning

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In cognitive planning, a student’s effective engagement is influenced by a combination of these
 1482 distances. We define a cognitive planning function

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$$C(i) = f(\{d(i, j)\}_{j \neq i}, d_T(i), d_B(i), \Omega(i)),$$

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1486

where $f(\cdot)$ aggregates peer proximity, teacher distance, and board distance together with additional
 1487 factors $\Omega(i)$ (e.g., individual motivation, prior knowledge, or task demands).

1488

1489

Thus, physical proximity among peers (as encoded in the seat graph) provides the structural baseline,
 1490 while teacher and board distances add instructional and attentional dimensions. These spatial factors,
 1491 combined with non-spatial determinants $\Omega(i)$, jointly shape the student’s cognitive planning process.

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C.1.5 CONFIGURATION SCHEMA AND PHYSICAL REALISM

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Our environment is instantiated on a two-dimensional grid of size 30×20 . Each classroom layout is
 1495 parameterized by a configuration schema, including layout type (*Lecture*, *Round Table*, or *Collaborative Two Tables*), table radius, table spacing, and object coordinates (students, teacher, podium, board,
 1496 and tables).

1497

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Peer adjacency is determined by a Euclidean distance threshold $\tau_d = 4.5$, with an additional tolerance
 1499 of +1.0 if two students belong to the same group. In the *Round Table* layout, opposite students
 1500 are explicitly connected, while in the *Collaborative* layout, within-table students form a complete
 1501 subgraph and inter-table connections are suppressed.

1502

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1504 Perception is bounded by a radius ($r = 8$) and a capacity constraint ($\kappa = 5$), ensuring that each student
 1505 can only attend to a limited number of peers or objects. Collision masks and occupancy constraints
 1506 are implicitly enforced by the grid representation, while actions violating spatial feasibility (e.g.,
 1507 moving into occupied cells or colliding with fixed objects) are rejected. This ensures reproducibility
 1508 and interpretability of spatially grounded interactions.

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C.2 DETAILED DESCRIPTION OF COGNITION ENGINE

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C.2.1 THEORETICAL FOUNDATIONS OF PCA ARCHITECTURE

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CIE adopts a three-stage **Perception–Cognition–Action (PCA)** architecture to simulate agent
 1513 decision-making (Chen et al., 2024a; Davis & Gao, 2003; Hancock et al., 1996; Yao, 2020). This

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1513
1514 Table A4: Functional differentiation between student and teacher agents in **CIE**.
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Component	Student Agent \mathcal{A}_S^i	Teacher Agent \mathcal{A}_T
Perception Input	Teacher actions, peer behavior, social re-quests, seat graph, interaction graph	Class-wide metrics, participation logs
Cognitive Objective	Interpret prompts, decide on participation	Track engagement, guide task flow
Action Output	Interactive action, Active action, Passive action, Off-task action	Task instruction, Interactive teaching acts
Triggering Condition	Willingness + gating check	Scripted plans + real-time updates
Prompt Conditioning	<i>Personalized traits</i> : personality, style, motivation	<i>Fixed templates</i> : instructional role

1525 design is grounded in both classical AI agent models and foundational theories in educational
1526 psychology, capturing the trajectory from environmental sensing to goal-directed behavior.

1527 From a psychological perspective, PCA aligns with the Atkinson–Shiffrin model of information
1528 processing (Atkinson & Shiffrin, 1968; Izawa, 1999; Cheng & Schwing, 2022) and resonates with
1529 constructivist and metacognitive theories of learning (Gunstone, 1992; Bonanno, 2004). It integrates
1530 affect, cognition, and behavior, emphasizing how learners perceive, interpret, and regulate actions in
1531 evolving classroom contexts.

1532 Within this structure, the **Perception** stage gathers contextual cues such as teacher prompts, peer
1533 behaviors, and environmental signals. The **Cognition** stage transforms these inputs into internal
1534 reasoning and action intent, and the **Action** stage executes verbal, physical, or social behaviors
1535 accordingly.

1536 A central innovation in CIE is the integration of a metacognitive loop—**Plan, Monitor, Regulate**—within the cognition stage. Student agents are not merely reactive: they proactively plan
1537 whether and how to act, monitor the clarity and outcomes of their behaviors, and regulate subsequent
1538 strategies based on feedback. For example, an agent may decide whether to speak (**Plan**), evaluate
1539 the appropriateness of its utterance (**Monitor**), and adjust behavior after receiving teacher feedback
1540 (**Regulate**). This bidirectional cycle links teacher interventions with student adaptations, producing
1541 temporally grounded learning trajectories that approximate authentic development.

1543 The same PCA structure extends to teacher agents, where cognitive stages underpin pedagogical
1544 decisions such as goal-setting, feedback selection, interpretation of class-level signals, and adjustment
1545 of emotional tone. This unified yet role-differentiated framework enables interpretable and traceable
1546 behaviors across heterogeneous agents.

1547 In summary, the PCA architecture provides a theoretically grounded, modular, and extensible control
1548 mechanism, serving as the cognitive backbone of the CIE framework.

1551 C.2.2 PERSONALITY-CONDITIONED COGNITION

1553 To capture individualized learning dynamics, CIE embeds a triadic psychological
1554 model—**personality traits, cognitive style, and learning motivation**—into each student
1555 agent’s cognition engine. This design ensures that agents are not only responsive to instructional
1556 context but also conditioned by stable psychological dispositions, thereby enabling heterogeneous
1557 patterns of planning, action execution, and self-regulation.

1558 This modeling approach is anchored in established educational psychology theories. (1) The *Big Five*
1559 *Personality Traits* inform dispositional tendencies such as agreeableness or conscientiousness (Gerber
1560 et al., 2011; Komarraju et al., 2011). (2) Dimensions like *Field Dependence–Independence* and
1561 *Impulsivity–Reflection* characterize cognitive style, shaping how learners process information and
1562 regulate decisions (Swinnen et al., 1986; Jamieson, 1992; Yang & Chen, 2023). (3) Motivational
1563 dimensions are guided by *Self-Determination Theory* and *Expectancy-Value Theory*, which capture
1564 intrinsic versus extrinsic drivers of engagement (Yue & Lu, 2022; Gladstone et al., 2022; Loh, 2019).
1565 Together, these constructs define how agents interpret classroom signals, prioritize goals, and sustain
1566 effort over time, even under identical task conditions.

1566 Each student agent is initialized with a structured personality profile encoded in JSON format,
 1567 including its trait vector, cognitive preferences, and motivational disposition. During execution, these
 1568 parameters are accessed primarily in the *Plan* stage of the PCA loop, guiding intention formulation
 1569 and prompt conditioning. For instance, a highly agreeable agent tends to produce affirming or
 1570 cooperative responses during group discussion, whereas a low-conscientiousness agent is more
 1571 likely to show task-avoidant tendencies. Reflective learners adopt deliberate monitoring strategies
 1572 and gradual adjustment, while impulsive learners often exhibit frequent shifts and inconsistent
 1573 participation.

1574 By embedding these individualized profiles into the cognitive control cycle, CIE generates agents that
 1575 combine **behavioral realism** with **systematic variability**. The heterogeneity among agents promotes
 1576 the simulation of authentic classroom dynamics, such as uneven participation or role differentiation.
 1577 Moreover, these embedded traits provide interpretable signals for teacher agents, enabling differentiated
 1578 instruction and context-sensitive feedback strategies. In this way, the personality-conditioned
 1579 cognition module supports both fine-grained behavioral modeling and pedagogical analysis, bridging
 1580 psychological theory with computational simulation.

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1582 **Virtual Student Profile: Wang Fang**

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Basic Information:

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- Age: 13 Gender: Female
- Spawn Position: (5, 1)
- Perception Config: Range = 3, Max Tracked Items = 5

Learning Engagement:

- Behavior = Head-down reading
- Emotion = Positive
- Cognition = Understanding

Personality Traits (Big Five):

- Personality Type: High Neuroticism
- Neuroticism: 0.9, Extraversion: 0.5, Agreeableness: 0.5, Openness: 0.5, Conscientiousness: 0.5

Cognitive Style:

- Field Independent
- Reflective

Learning Motivation: High

Class Role: Academic-Oriented Student

Behavior Profile:

- **Language Style:** Hesitant, emotionally influenced; uses fillers like “um”, backtracks responses, shows fragmented expression.
- **Class Behavior:** Anxious under pressure; avoids raising hand but listens attentively in groups; completes work slowly but with logical clarity and strong motivation.
- **Learning Preference:** Prefers independent tasks, reflective practice; likes using notes or diagrams for organizing knowledge; enjoys self-paced deep exploration.
- **Teacher Guidance:** Reduce performance anxiety via timely feedback; provide structured task breakdowns and staged learning goals; encourage written or non-verbal responses.
- **Role Description:** Acts as knowledge summarizer in groups; organizes ideas clearly; prefers private channels for expressing ideas to build confidence.

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C.2.3 PERSONALITY-DRIVEN STYLE MODULATION

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To ensure that agents maintain trait-aligned consistency in language and behavior generation across multi-turn interactions, **CIE** introduces a dual-module mechanism: the **Style Modulator** and the **Cognitive Generator**. This design balances the generalization strength of large language models (LLMs) with the need for personality-conditioned expression, thereby ensuring that each virtual student consistently exhibits distinctive communicative styles and cognitive tendencies during simulation.

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Style Modulator. We adopt multimodal large models (InternVL (Chen et al., 2024b), Qwen (Bai et al., 2023), MiniCPM (Hu et al., 2024), and LLaVa (Li et al., 2024a)) as the linguistic foundation for virtual students. Although these models support visual inputs, in this work we use only their language-generation modules, as the core task is to produce persona-consistent classroom utterances within EduVerse. We choose VLMs rather than pure LLMs to ensure future extensibility, since EduVerse will later incorporate multimodal instructional materials and nonverbal classroom cues. To select the primary generator, we first evaluated all candidates on Chinese language-instruction tasks, assessing text understanding and text reconstruction accuracy on middle-school materials. InternVL achieved the strongest baseline performance. We then conducted persona fine-tuning (Hu et al., 2021) using more than 6,000 real classroom utterances covering multiple instructional phases and questioning modes. Post-fine-tuning evaluation, combining human judgments and large-scale GPT-4 scoring, showed that InternVL produced the most stable and distinctive learner styles. We therefore adopt InternVL as the main student model and fine-tune it using LoRA.

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Cognitive Generator. At each stage of the metacognitive loop—*Plan, Monitor, Regulate*—the system issues role-specific prompts that drive context-aware decision-making. These prompts integrate the agent’s personality profile, current instructional signals, and historical behavioral traces, thereby enabling dynamic adjustment of cognitive strategies. Prompt templates are separately designed for student and teacher agents, supporting the complete perception–cognition–action loop described in earlier sections.

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Overall, this dual-module design not only enhances the realism and stability of personality-conditioned expression but also provides an interpretable framework for modeling diverse educational behaviors in simulated classrooms.

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Plan Prompt for Virtual Student Agent

You are a student named `{self.name}`, and your character profile is `({self.profile})`. Based on your persona and the following contextual information, reflect on your learning goal and behavioral plan in the current class session:

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- Current physical distance: `{self.profile['dist_teacher']}`, `{self.profile['dist_blackboard']}`
- Teacher’s current behavior: `{teacher_behavior}`
- Teacher’s emotional tone: `{teacher_emotion}`
- Teacher’s instructional content: `{teacher_content}`
- Other students’ previous standing responses: `{stu_response}`
- Previous student questions to the teacher: `{stu_request}`
- Learning status of neighboring classmates: `{neighbors}`
- Relevant instructional objects: `{objects}`
- Your recent learning experiences and regulation suggestions: `{memory[:3]}`
- Your personality type: `{self.personality_type}`
- Your learning behavior style: `{self.class_behavior}`
- Your classroom role: `{self.class_role}`
- Current lesson content: `{self.shared_state['lesson_content']}`

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Based on the above information and your personality traits, describe your behavioral plan using a first-person reasoning chain. The behavior must fall into one of the following four categories:

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- **Active behaviors:** taking notes, raising hand
- **Passive behaviors:** listening attentively, reading silently, reading aloud
- **Interactive behaviors:** side talk with peers, asking the teacher questions
- **Disengaged behaviors:** sleeping on desk, chatting with others

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1696**Instructions:**

1. Carefully consider the teacher's state, peer learning status, your persona, and recent self-regulation experience.
2. Your behavior should align with your habitual classroom pattern—e.g., if you are disengaged by nature, plan accordingly, unless your self-regulation history indicates change.
3. Output must follow a first-person reasoning chain—concise and limited to a single sentence.
4. Select **only one final behavior** from the list (e.g., taking notes / raising hand / listening attentively / reading silently / reading aloud / side talk / asking questions / sleeping / chatting).
5. Strictly follow the output format below:

The teacher is asking about spring-related poetry, with a calm tone. My neighbors are actively raising their hands XXXX.

Final behavior: side talk with peers

1697
1698**Monitor Prompt for Virtual Student Agent**1699
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You are a student named `{self.name}`, and your character profile is `({self.profile})`. Based on your persona and the following contextual information, reflect on the current instructional situation and evaluate whether your understanding and behavior are appropriate:

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- Teacher's behavior: `{teacher_behavior}`
- Neighboring student states: `{neighbors}`
- Your previous plan: `{plan_output}`
- Recent memory fragments: `{memory}`
- Your current behavior: `{action_result.get('behavior', 'unknown')}`
- Feedback received: `{action_result.get('response', 'none')}`
- Your personality type: `{self.personality_type}`
- Your classroom behavior habit: `{self.class_behavior}`

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Based on the information above, assess your current emotional and cognitive state under the behavior you just performed. Emotions should be classified into three categories: **positive**, **negative**, or **confused**. Cognitive states should follow Bloom's taxonomy and be selected from: **Remembering, Understanding, Applying, Analyzing, Evaluating, Creating**.

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1719
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1722
1723**Instructions:**

1. Briefly monitor your behavioral process using a first-person perspective.
2. Output your emotional and cognitive category results strictly in the following format:
I think XXX
Emotion: XXX
Cognition: XXX

1724
1725
1726
1727**Regulate Prompt for Virtual Student Agent**

You are a student named `{self.name}`, and your character profile is `{self.profile}`. Based on your persona, your recent monitoring reflection (`{monitor_output}`), memory state (`{memory}`),

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and the teacher's feedback (*{teacher_feedback}*), reflect on what adjustment strategy you should adopt next (e.g., asking a question, taking notes, communicating with peers, etc.).

Additional contextual information:

- Teacher's current behavior: *{teacher_behavior}*
- Your personality type: *{self.personality_type}*
- Your classroom learning habits: *{self.class_behavior}*
- Current social interaction partners: *{self.shared_state["social_interaction"]}*
- Peers who rejected your conversation attempts: *{social_request_reject}*

Instructions:

1. Briefly analyze how you would like to adjust your learning strategy in the next step.
2. The output should be concise and stated in the first person, using only one sentence.

Example: "I got distracted just now, and the teacher called on me; I hope to refocus and pay better attention."

Prompt for Virtual Teacher: Reconstructing Lesson Plan into Instructional Phases

You are an experienced and professional middle school Chinese language teacher. Below is the instructional plan for the lesson titled *{self.lesson_id}*. Please read the lesson plan carefully and reconstruct it according to the required structure.

Task: Carefully review the content of the *{self.lesson_id}* lesson plan. Reorganize the instructional content into five standard teaching phases: **Lesson Introduction, New Content Instruction, Knowledge Consolidation, In-Class Practice, and Lesson Summary**.

The lesson consists of a total of 30 time steps. For each phase:

- Provide a concise summary of the instructional content to be covered, written in paragraph form (no bullet points), within 50 characters (or equivalent).
- Allocate a specific number of time steps to each phase.

Lesson Plan Content:

```
--- Lesson Plan Start ---
{self.lesson_plan_text}
--- Lesson Plan End ---
```

Please strictly follow the output format below:

```
Lesson Introduction: XXXX, Steps: XXX
New Content Instruction: XXXX, Steps: XXX
Knowledge Consolidation: XXXX, Steps: XXX
In-Class Practice: XXXX, Steps: XXX
Lesson Summary: XXXX, Steps: XXX
```

Prompt for Virtual Teacher: Instructional Step Planning

You are an experienced and professional middle school Chinese language teacher. You are currently teaching the course *{self.lesson_id}* and are now in the instructional phase titled "*{teaching_phase}*". Please plan the instructional content for this specific phase.

This phase is expected to span *{total_steps}* instructional steps. Below is a brief summary of the content you are expected to teach in this phase: *{teaching_phase}*

Instructions:

1. Break down the above instructional content into **{total_steps}** individual teaching steps.
2. Each step should consist of one concise sentence (no more than 20 Chinese characters or equivalent length in English).
3. Ensure that each step aligns clearly with the goal of the current instructional phase.

1782
 1783 4. Avoid repetition, vague statements, or logical leaps between steps.
 1784 5. Use the following format for output:
 1785
 1786 1. xxx
 1787 2. xxx
 1788 3. xxx
 1789 ...
 1790
 1791

Prompt for Virtual Teacher: Selecting Instructional Behavior Type

1792 You are an experienced and professional middle school Chinese language teacher. You
 1793 are currently teaching the lesson *{self.lesson_id}*, and are now in the instructional phase
 1794 "*{phase}*". The content planned for the current time step is: *{teaching_step_content}*.
 1795 Please determine the most appropriate instructional behavior type based on the following
 1796 contextual information:
 1797

1798
 1799 • Student participation, emotional, and cognitive states: *{percep-*
 1800 *tion_result['teaching']['statistics']}*
 1801 • Your most recent teaching feedback: *{teacher_feedback}*
 1802 • Student self-regulation output: *{student_regulation}*
 1803 • Your last behavior category: *{category}*
 1804

Instructions:

1805
 1806 1. Consider whether to maintain or shift from your previous behavior category (*{cate-*
 1807 *gory}*).
 1808 2. It is generally preferred to vary your instructional strategy across consecutive time
 1809 steps for richer pedagogical dynamics.
 1810 3. Select one behavior category from the following list:
 1811
 1812 • Classroom Instruction (e.g., lecturing, giving directions)
 1813 • Classroom Interaction (e.g., expressing emotion, praise, incorporating student
 1814 input, asking questions, giving criticism, organizing discussion)
 1815 • Classroom Behavior Management (e.g., addressing students sleeping or chat-
 1816 ting)
 1817 4. **Important:** Output only the final selected category name without numbers. *For*
 1818 *example:* Classroom Interaction
 1819
 1820

Prompt for Virtual Teacher: Selecting Fine-Grained Teaching Action

1821 You are an experienced and professional middle school Chinese language teacher. You are
 1822 currently teaching the lesson *{self.lesson_id}* and are in the instructional phase "*{phase}*".
 1823 The planned instructional content for the current time step is: *{teaching_step_content}*.
 1824 You have decided to perform a *{category}* type of teaching behavior. Based on the following
 1825 contextual information, please select one fine-grained instructional action that aligns with
 1826 your selected behavior type.
 1827

1828
 1829 • Current phase: *{phase}*
 1830 • Behavior type selected: *{category}*
 1831 • Student participation and emotional state: *{percep-*
 1832 *tion_result['teaching']['statistics']}*

Available fine-grained behaviors by category:

1833
 1834 • **Classroom Instruction:** lecturing, giving directions
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- **Classroom Interaction:** expressing emotion, praising, adopting student input, asking questions, giving criticism, organizing group discussion
- **Classroom Behavior Management:** addressing students sleeping, addressing students chatting

Instructions:

- Select only one fine-grained behavior that best suits the context.
- Do not include any numbering or extra explanation.
- *Example:* lecturing

Prompt for Virtual Teacher: Generating Instructional Utterance

You are an experienced and professional middle school Chinese language teacher. You are currently teaching the lesson `{self.lesson_id}`, and are in the instructional phase "`{phase}`". The instructional content planned for this time step is approximately: `{teaching_step_content}`. Your selected teaching behavior is: `{behavior}`. Please generate the instructional utterance you will deliver to students based on the following context:

- Current instructional phase: `{phase}`
- Teaching behavior: `{behavior}`
- Planned teaching content for this time step: `{teaching_step_content}`
- Current student states: `{perception_result['teaching']|['statistics']}`
- Recent content already covered: `{[h['content'] for h in history[-3:]}|}`
- Text material being taught: `{self.shared_state['lesson_content']}`

Instructions:

1. Your utterance must logically follow previously delivered content and align with the current teaching goal.
2. **Avoid repeating prior statements.**
3. If your behavior is **lecturing**, you may deliver up to 5 informative sentences focused on knowledge delivery.
4. For all other behavior types, limit the output to **2–3 sentences**.
5. You may refer to specific students based on what you know about them (e.g., call them by name), except when the behavior is **organizing classroom discussion**. In that case, pose an open-ended prompt to all students, optionally setting up a collaborative or competitive task.

Please output only the generated utterance (no metadata).

Prompt for Virtual Teacher: Selecting Instructional Emotion

You are an experienced and professional middle school Chinese language teacher. You are currently teaching the lesson `{self.lesson_id}` and are in the instructional phase "`{phase}`". The teaching content for the current time step is: `{content}`, and your current instructional behavior is: `{behavior}`.

Please determine the most appropriate emotional tone for this moment based on the following student emotional state:

- Student emotional distribution: `{emo}`

Instructions:

- Choose one emotional tone from the following three options:
 - **Encouraging**
 - **Critical**

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1943**– Neutral**

- Please output **only one** of the three tones, with no additional explanation.
- *Example output: Encouraging*

To ensure stylistic and semantic consistency across multi-turn dialogues, **CIE** introduces a mechanism that aligns dialogue history with continuity of style. Specifically, the output generated at each *Regulate* stage is propagated forward into the subsequent *Plan* stage, thereby preserving coherence in both personality expression and cognitive trajectory. Response generation follows a hybrid pipeline: a LoRA-tuned LLM first produces a personality-aligned draft, which is then refined by GPT-4 to guarantee pedagogical validity and cognitive plausibility. This dual-stage strategy integrates personality intent, cognitive structure, and contextual awareness into a unified and adaptive response process.

Prompt for Personality-Driven Style Modulation

You are an assistant that can revise student responses based on their personality characteristics while preserving their individual speaking style.

The student's personality type is: *{self.personality_type}*. Below is a one-sentence sample response in their characteristic style. Your task is to refine it based on the student's persona without altering the style.

Student Information:

- Name: *{self.name}*
- Personality Type: *{self.personality_type}*
- Language Style: *{self.language_style}*
- Classroom Behavior: *{self.class_behavior}*

Context:

- Teacher's question: *{query}*
- The student plans to raise their hand to respond.
- Their drafted response: *{draft}*
- Learning plan for this time step: *{plan}*

Instructions:

1. Evaluate whether the drafted response is reasonable. If it is not, you may disregard it and instead generate a new answer based on the student's personality traits.
2. Middle school students typically speak concisely—your revised response should follow similar length and tone as the sample.
3. Your final output should:
 - Maintain the student's original speaking style;
 - Reflect their personality and classroom behavior;
 - Align with the current instructional context.
4. **Output only the revised response.**

C.3 DETAILED DESCRIPTION OF SOCIAL SITUATEDNESS**C.3.1 THEORETICAL EXPANSION OF IRF PARADIGM**

The Initiation–Response–Feedback (IRF) model, first proposed by Sinclair and Coulthard, remains a cornerstone in classroom discourse analysis (Waring, 2009; Rustandi, 2017). It organizes interaction into three stages: the teacher *initiates* with prompts or questions (I), the student *responds* verbally or behaviorally (R), and the teacher provides *feedback* (F) in the form of evaluation or elaboration. While concise and widely applicable, this formulation is limited in capturing the cognitive and social dynamics of modern classrooms.

1944 Under constructivist and inquiry-oriented pedagogies, students act as reflective learners rather than
 1945 passive recipients (Walker & Shore, 2015; Renninger, 2024). They monitor, regulate, and socially
 1946 negotiate their learning in response to both internal states and external cues—capacities insufficiently
 1947 represented in the original IRF framework.

1948 To address this gap, **CIE** extends IRF into a four-phase structure, termed IRF-R, by introducing a
 1949 **Regulation** stage. After receiving feedback, students engage in metacognitive processing: reassess-
 1950 ing their performance, adjusting goals, and modifying strategies in light of emotional state, peer
 1951 interaction, and task relevance. In this expanded cycle, *Initiation* stimulates attention and motivation,
 1952 *Response* generates verbal or behavioral engagement, *Feedback* reinforces or redirects cognition, and
 1953 *Regulation* transforms feedback into adaptive behavior.

1954 The IRF-R paradigm thus supports multi-turn interaction loops that conceptualize learning as a
 1955 continuous cycle of stimulation, expression, feedback, and self-adjustment. It enables teacher agents
 1956 to track not only immediate responses but also downstream learning adjustments, thereby improving
 1957 the interpretability of student behavior and supporting deeper trajectories of engagement.

1959 C.3.2 IMPLEMENTATION OF SOCIAL PRIORITIZATION

1961 In the **CIE** multi-agent system, student agents must simultaneously handle instructional prompts
 1962 from teacher agents and spontaneous peer-initiated interactions during lessons. To resolve conflicts
 1963 among these competing inputs, we introduce a **social prioritization mechanism** inspired by gated
 1964 decision control. This ensures that at each time step, every agent responds to the interaction with the
 1965 highest *pedagogical relevance* (see Alg. A.1).

1967 **Algorithm A.1: Social Priority Gating Mechanism**

1968 **Input:** Local perception $s_{i_p}^t$ of agent i , shared state S , social threshold θ

1969 **Output:** Behavioral decision a_i^t

```

1971 1 if TeacherRequestExists( $i, s_{i_p}^t$ ) then
1972 2    $a_i^t \leftarrow$  respond to teacher (e.g., “stand and answer”);
1973 3   RejectSocialRequest( $i$ , ‘Teacher Priority’);
1974 4 else if SocialRequestExists( $i, S$ ) then
1975 5    $r_i^t \leftarrow$  GetSocialRequest( $i, S$ );
1976 6    $H_{i,j}, S_{i,j} \leftarrow$  AnalyzeChatHistory( $i, r_i^t$ .from_id);
1977 7    $W_i^t \leftarrow$  ComputeIntention( $P_i, C_i, R_i, H_{i,j}, S_{i,j}$ );
1978 8   if  $W_i^t \geq \theta$  then
1979 9      $a_i^t \leftarrow r_i^t$ .type;
1980 10     $r_i^t$ .status  $\leftarrow$  accepted;
1981 11  else
1982 12     $a_i^t \leftarrow$  Self-Initiated Learning;
1983 13    RejectSocialRequest( $i$ , ‘Low Intention’);
1984 14 else
1985 15   $a_i^t \leftarrow$  Self-Initiated Learning;
1986 16 return  $a_i^t$ ;

```

1988 Interaction priorities are structured into three tiers. First, **teacher requests** (e.g., direct questioning
 1989 or task assignments) override all other interactions, placing the student agent in an uninterrupted
 1990 execution state. Second, if no teacher request is present, the agent evaluates **peer requests** and **group**
 1991 **discussions** (e.g., side chats, peer questions). Here, an LLM-based reasoning process integrates
 1992 personality traits, task context, and interaction history to compute a *social willingness score* $W_i^t \in$
 1993 $[0, 1]$. If $W_i^t \geq \theta$ (e.g., $\theta = 0.6$), the request is accepted; otherwise, it is rejected and the agent returns
 1994 to self-regulated learning. Third, in the absence of external input, the agent continues self-initiated
 1995 planning and behavior execution.

1996 To ensure transparent tracking, all requests are logged in the shared interaction state pool with one of
 1997 three tags: **Pending** (awaiting response), **Accepted** (engagement initiated; dialogue content logged
 for future reasoning), or **Rejected** (declined without side effects; agent resumes autonomous learning).

1998 This tagging protocol enables fine-grained regulation of peer dialogue without disrupting the core
 1999 instructional flow.

2000 Overall, the gating-based prioritization mechanism preserves instructional coherence while still
 2001 allowing socially grounded behaviors to emerge adaptively and contextually in classroom simulations.
 2002

2003 C.3.3 SOCIAL INTENTION FUNCTION

2005 In multi-agent classroom environments, modeling whether a student agent is willing to accept peer-
 2006 initiated interactions is crucial for simulating realistic social behavior. To this end, **CIE** introduces
 2007 a language model–driven **Social Intention Function**, which dynamically determines willingness
 2008 based on the current instructional context. This function integrates five factors—personality traits,
 2009 learning confidence, task relevance, historical interaction frequency, and social closeness—into a
 2010 context-aware decision process.

2011 To ensure educational interpretability, each factor is anchored in established psychological theories:
 2012

- 2013 • **Personality Match (P):** Following the *Big Five Personality Theory*, students high in
 2014 extraversion tend to be socially responsive, while those high in neuroticism are more likely
 2015 to avoid interaction (Zhao & Seibert, 2006; John et al., 1999).
- 2016 • **Current Learning Confidence (C):** Based on *Bandura’s Self-Efficacy Theory*, confidence
 2017 in task performance directly shapes one’s propensity for social engagement (Schunk &
 2018 DiBenedetto, 2016; Bandura & Adams, 1977).
- 2019 • **Task Relevance (R):** Grounded in *Situated Cognition* and *Constructivist Learning Theory*,
 2020 this factor assesses whether a social request aligns with the ongoing instructional
 2021 objective (Wilson & Myers, 2000; Hedegaard, 1998).
- 2022 • **Historical Interaction Frequency (H) and Social Closeness (S):** Informed by *Social Identity Theory*,
 2023 these capture group belonging and accumulated positive peer interactions (Hogg,
 2024 2016; Ellemers & Haslam, 2012).

2026 Each component is scored within the range [0, 100] using GPT-4 via fine-tuned prompts, represented
 2027 as P, C, R, H, S . Simultaneously, the system generates a context-dependent weight vector:

$$2028 \quad \alpha = [\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5], \quad \text{subject to} \quad \sum_{i=1}^5 \alpha_i = 1. \quad (4)$$

2032 The model also outputs a short justification for each weight to enhance interpretability. The final
 2033 **Social Intention Score** is computed as:

$$2034 \quad W = \alpha_1 P + \alpha_2 C + \alpha_3 R + \alpha_4 H + \alpha_5 S. \quad (5)$$

2036 If $W \geq 0.6$ (default threshold), the student accepts the request and enters a dialogue; otherwise, the
 2037 request is rejected and the agent resumes self-directed learning.
 2038

2039 This mechanism functions not merely as a scoring model, but as a cognitively and socially grounded
 2040 reflection of student behavior. It captures a learner’s “social rationality” and “regulatory capacity”
 2041 across tasks and roles, enhancing both the behavioral realism and interpretability of CIE’s agent-based
 2042 interaction model.

2043 C.4 DETAILED DESCRIPTION OF TEMPORAL DYNAMICS

2044 C.4.1 THEORETICAL FOUNDATIONS OF AGENT STATE PROGRESSION AND REGULATION

2047 In **CIE**, the learning process of virtual students is conceptualized not as isolated one-step reactions
 2048 but as a temporally extended trajectory unfolding across multiple time steps. This trajectory re-
 2049 flects progressive **cognitive development**, **emotional regulation**, and **behavioral adaptation**. To
 2050 capture these dynamics, we introduce a dual mechanism of **State Progression** and **State Regu-**
 2051 **lulation**, grounded in established theories of educational psychology, thereby modeling agent-level
 development across lessons and instructional phases.

2052 **Cognitive development** is anchored in Bloom’s Taxonomy (Krathwohl, 2002; Forehand, 2010) and
 2053 Bruner’s Spiral Curriculum (Clark, 2010; Joseph, 2021). Bloom’s hierarchy delineates a progression
 2054 from lower- to higher-order cognition:

2055 Remembering → Understanding → Applying → Analyzing → Evaluating → Creating.
 2056 In CIE, each student agent’s cognitive output is annotated accordingly at each step, enabling temporal
 2057 trend analysis. Complementarily, Bruner’s spiral principle emphasizes cyclical revisiting of concepts
 2058 with increasing complexity, allowing longitudinal tracking of knowledge deepening, reinforcement,
 2059 and occasional regression.

2060 **Emotional and behavioral adaptation** is informed by Emotion Regulation Theory (Gross, 2008;
 2061 1999), Self-Determination Theory (SDT) (Deci et al., 2017; Deci & Ryan, 2012), and Ex-
 2062 pectancy–Value Theory (Wigfield, 1994; Wigfield & Eccles, 2000). Gross highlights that learners
 2063 regulate emotions through strategies such as support-seeking, withdrawal, or task switching. In CIE,
 2064 these processes shape the `Regulate` module, where agents evaluate affective states to guide strate-
 2065 gic adjustment. SDT introduces autonomy, competence, and relatedness as motivational parameters;
 2066 these are embedded into CIE’s motivation and social intention functions, influencing persistence and
 2067 behavioral shifts across time. Expectancy–Value perspectives further explain how perceived value
 2068 and anticipated success jointly determine sustained engagement.

2069 **Teacher–student feedback dynamics** build upon Hattie and Timperley’s Feedback Model (Hattie &
 2070 Timperley, 2007b) and Vygotsky’s Sociocultural Theory (Lantolf, 2000; Scott & Palincsar, 2013).
 2071 The former stresses that effective feedback triggers metacognitive reassessment and regulation beyond
 2072 error correction; in CIE, such feedback modifies both goal-setting and emotional states in subsequent
 2073 Plan phases. Vygotsky’s theory adds a social dimension: knowledge construction is mediated by
 2074 interaction, and teacher or peer feedback indirectly shapes confidence, regulation, and discourse
 2075 strategies.

2076 In summary, the integration of state progression and regulation mechanisms allows CIE to simulate
 2077 learning as a temporally grounded, theory-consistent developmental process. Virtual students are
 2078 thus modeled not as reactive output devices but as evolving educational agents whose longitudinal
 2079 behavioral trajectories provide interpretable evidence of learning dynamics and cognitive pathway
 2080 development.

2081 C.4.2 TEACHER-CONTROLLED INSTRUCTIONAL PACING

2084 **Algorithm A.2:** Teacher-controlled Instructional Phase Pacing

2085 **Input:** Current instructional phase Phase_k , student state set $\{s_i^t\}_{i=1}^n$, step count t
 2086 **Output:** Next instructional phase Phase_{k+1}

2087 1 Initialize total steps per phase: $T \leftarrow 30$;
 2088 2 Initialize current step index: $t \leftarrow 1$;
 2089 3 Initialize teacher policy: π_T ;
 2090 4 **while** $t \leq T$ **do**
 2091 5 Observe group student state $S^t = \{s_i^t\}_{i=1}^n$;
 2092 6 Execute teacher action $a_T^t \sim \pi_T(S^t, \text{Phase}_k)$;
 2093 7 Broadcast action a_T^t to all student agents ;
 2094 8 Collect responses and update S^{t+1} ;
 2095 9 $t \leftarrow t + 1$;
 2096 10 Evaluate completion rate: $r_k \leftarrow \text{Evaluate}(S^t)$;
 2097 11 Determine transition: $\text{Phase}_{k+1} \leftarrow \text{Transition}(\text{Phase}_k, S^t, r_k)$;
 2098 12 **return** Phase_{k+1}

2099 In multi-step instructional simulations, effective pacing control is essential not only for synchronizing
 2100 with students’ learning rhythms but also for maintaining interactional coherence and managing
 2101 cognitive load. To address this challenge, the **CIE** framework incorporates a **Teacher Agent Rhythm**
 2102 **Control Module**, which dynamically governs the progression of instructional phases throughout a
 2103 lesson.

2104 Each lesson is preconfigured into five canonical instructional phases (e.g., introduction, explanation,
 2105 consolidation), further decomposed into discrete teaching steps. During simulation, the teacher

2106 agent adaptively decides whether to continue, delay, or advance phase transitions based on real-time
 2107 classroom signals rather than following a fixed timeline.
 2108

2109 This decision process operates through a **Perception–Cognition–Action (PCA)** loop. At each step t ,
 2110 the teacher agent first perceives aggregated student states $S^t = \{s_i^t\}_{i=1}^n$ (e.g., participation density,
 2111 emotional distribution, cognitive indicators). In the cognition stage, it evaluates whether the current
 2112 phase Phase_k should be sustained or transitioned by integrating lesson plan constraints, system logs,
 2113 and recent feedback. Finally, the action stage executes the pacing decision, broadcasting teacher
 2114 actions a_T^t and updating the global state.
 2115

2116 The pacing controller thus implements a data-driven mechanism that ensures phase boundaries remain
 2117 pedagogically aligned and interpretable across the session. Each time step is explicitly logged with
 2118 its transition rationale, enabling post-hoc analysis and iterative refinement of instructional design.
 2119 The full scheduling logic is summarized in Alg. A.2.
 2120

2120 C.5 MEMORY MECHANISMS FOR AGENT COGNITION

2121 C.5.1 THEORETICAL FOUNDATIONS OF MEMORY MECHANISMS

2122 In cognitive psychology and the learning sciences, memory mechanisms are central to understanding
 2123 how learners encode, retain, and retrieve knowledge for decision-making (Terry, 2017; Sprenger,
 2124 1999). To simulate this process in virtual agents, CIE implements a dual-layer memory architecture
 2125 inspired by the classical *Working Memory–Long-Term Memory* model. This design ensures both
 2126 real-time responsiveness and cross-session continuity in agent cognition and behavior.
 2127

2128 **Working memory** provides short-term storage of salient instructional information during ongoing
 2129 sessions—such as teacher actions, peer interactions, emotional states, and cognitive indicators.
 2130 These records are stored in a global `shared_state` structure, which is updated at each time
 2131 step t . This memory layer enables the real-time execution of the *Perception–Cognition–Action*
 2132 (*PCA*) loop, featuring high temporal resolution and frequent access, thereby forming the basis for
 2133 moment-to-moment decision-making.
 2134

2135 **Long-term memory**, in parallel, functions as a persistent repository of knowledge accumulation
 2136 and behavioral trajectories. Implemented as a structured database, it logs each student’s historical
 2137 records across lessons, including cognitive progression, emotional trends, and task engagement. At
 2138 the beginning of each new session, the long-term memory is reloaded into the `shared_state`,
 2139 enabling agents to adapt based on prior experiences. This mechanism supports *experience-informed*
 2140 *learning* and retrospective reasoning across multiple episodes.
 2141

2142 By integrating these two layers, CIE models both the ephemeral and cumulative aspects of learning.
 2143 The separation between rapidly evolving working states and persistent knowledge encoding ensures
 2144 that agents can respond fluidly to the immediate instructional context while also continuously adapting
 2145 to their developmental history. The following sections provide a detailed description of the design
 2146 and flow between these two memory layers.
 2147

2148 C.5.2 IMPLEMENTATION OF SHORT-TERM SHARED MEMORY

2149 In CIE, the short-term memory mechanism—termed **short-term shared memory**—defines a unified
 2150 interaction state pool, `shared_state`, which facilitates high-frequency, real-time information
 2151 exchange among all agents, including both students and teachers. Drawing inspiration from the
 2152 psychological construct of working memory, this module temporarily stores task-relevant perceptual
 2153 information and cognitive-affective states within the current instructional phase, thereby enabling
 2154 synchronized decision-making across agents.
 2155

2156 The `shared_state` consists of several structured components, initialized at the start of each
 2157 session:
 2158

- 2159 • **Teacher state:** records the teacher’s current behavior, utterances, and emotional tone.
- **Request pools (instructional & social):** manage the lifecycle of agent-to-agent interaction
 2160 requests, including initiation, acceptance, and rejection.

- 2160 • **Student logs**: capture each agent’s cognitive level, emotional state, and behavior trace at
2161 every time step t .
- 2162 • **Spatial state**: represents agent-specific surroundings and perceptible objects, grounding
2163 interactions in physical context.
- 2164 • **Task & group context**: contains the active lesson plan, group composition, and instructional
2165 content segments.
- 2166 • **Interaction history**: maintains continuity of dialogue rounds and the evolution of collabora-
2167 tive strategies.
- 2168 • **Long-term memory reference**: integrates episodic summaries from previous lessons to
2169 initialize experience-informed behaviors.

2170
2171 This state pool is updated dynamically at each instructional step. For example, when a student
2172 initiates a peer request, the entry is appended to the social pool; when the teacher provides feedback,
2173 the teacher state is refreshed; when students respond, their logs are updated with behavioral and
2174 cognitive annotations. This continuous update cycle ensures that all agents maintain a synchronized
2175 representation of the evolving classroom environment.

2176 In summary, the short-term shared memory functions as the temporal backbone of coordinated
2177 multi-agent interaction in CIE. By supporting real-time perception and regulation within the Percep-
2178 tion–Cognition–Action loop, it enables adaptive and coherent decision-making in high-frequency
2179 educational scenarios.

2180 C.5.3 IMPLEMENTATION OF LONG-TERM MEMORY

2181 To sustain behavioral continuity and cumulative cognitive development across sessions, CIE
2182 incorporates a structured **long-term memory system** consisting of two SQLite databases:
2183 `student_memory.db` and `teacher_memory.db`. These databases respectively record student
2184 learning trajectories and teacher instructional behaviors over time.

2185 **Student Memory**: The `student_memory.db` contains a `long_term_memory` table with the
2186 following schema:

- 2187 • `student_id`: unique identifier for each student agent.
- 2188 • `event_type`: type of record (e.g., *Cognitive Planning, Monitoring, Regulation, Behav-*
2189 *ioral Record*).
- 2190 • `event_content`: natural language logs produced during metacognitive stages, including
2191 goal setting or strategic reflection.
- 2192 • `timestamp`: temporal marker that enables reconstruction of student-specific learning
2193 sequences.

2194 This structure ensures traceability of self-regulated learning activities, forming a temporally grounded
2195 chain along the *Perception–Cognition–Action* loop.

2196 **Teacher Memory**: The `teacher_memory.db` mirrors this design, maintaining a
2197 `long_term_memory` table that logs instructional records at the phase level:

- 2198 • `teacher_id`: unique identifier for the teacher agent.
- 2199 • `lesson_id`, `phase`: identifiers of the lesson and instructional phase.
- 2200 • `event_type`: type of teacher behavior (e.g., *Instructional Planning, Feedback*).
- 2201 • `content`: natural language descriptions of teacher intentions, evaluations, and scaffolding
2202 strategies.
- 2203 • `timestamp`: time of execution, supporting longitudinal modeling of instructional dynam-
2204 ics.

2205 A particular focus is placed on feedback chains (e.g., student question → teacher evaluation → student
2206 regulation), which provide the basis for context-aware instructional planning in future sessions and
2207 adaptive modeling of scaffolding behaviors.

2214 Together, these two databases enable bidirectional memory transfer: teacher agents analyze longitudinal
 2215 patterns in student performance, while student agents draw upon accumulated knowledge, goals,
 2216 and feedback to guide future behavior. The long-term memory system thus allows CIE to simulate
 2217 instructional interaction as an evolving and authentic temporal process.
 2218

2219 C.5.4 MEMORY INTERACTION FLOW

2220 To support cognitive development and behavioral adaptation across instructional sessions, CIE implements
 2221 a structured **Memory Interaction Flow** that coordinates short-term and long-term memory.
 2222 This mechanism enables student agents to accumulate, apply, and evolve learning experiences within
 2223 and across sessions, thereby sustaining coherence and continuity in personalized learning trajectories.
 2224

2225 At the start of each session, the system loads individual long-term memory summaries—such
 2226 as prior performance, cognitive tendencies, and emotional traits—from the database into the
 2227 `shared_state`. These values immediately inform in-session planning and response generation.

2228 During instruction, student agents continuously update the short-term memory at each time step
 2229 by recording their actions, peer interactions, and teacher feedback. These records ensure real-time
 2230 context awareness and guide micro-level cognitive regulation.

2231 At the end of a session, the system aggregates time-step records into structured learning summaries.
 2232 These include updated cognitive markers, emotional trajectories, and selected behavior patterns,
 2233 which are written back into the long-term memory for use in subsequent sessions.

2234 This continuous memory flow enables student agents to engage in feedback-informed, data-driven
 2235 self-regulation. Over time, they develop individualized learning patterns reflective of authentic
 2236 developmental trajectories in classroom environments. The complete execution logic of this flow is
 2237 outlined in Alg. A.3.

2239 **Algorithm A.3: Memory Interaction Flow for Agent i**

2240 **Input:** Agent ID i , shared state S , current step t , total steps T

2241 **Output:** Updated shared state S

```

2242 1 if  $t = 1$  then
2243 2    $L_i \leftarrow \text{DATABASE.retrieve\_long\_term\_summary}(i);$ 
2244 3    $S[\text{longterm\_summary}][i] \leftarrow L_i;$ 
2245
2246 4    $S[\text{interaction\_log}][i][t] \leftarrow \{$ 
2247 5      $\text{teacher\_interactions} : s_i^t.\text{teacher\_content},$ 
2248 6      $\text{social\_interactions} : s_i^t.\text{social\_requests},$ 
2249 7      $\text{student\_responses} : s_i^t.\text{stu\_response},$ 
2250 8      $\text{student\_requests} : s_i^t.\text{stu\_request},$ 
2251 9      $\text{environment\_context} : s_i^t.\text{visible\_items},$ 
2252 10     $\text{emotional\_states} : s_i^t.\text{teacher\_emotion},$ 
2253 11     $\text{cognitive\_states} : \text{MEMORY.retrieve\_cog}()$ 
2254 12  }
```

```

2255 13 if  $t = T$  then
2256 14    $M_i \leftarrow \text{Summarize\_Session}(S[\text{interaction\_log}][i]);$ 
2257 15    $\text{DATABASE.store\_long\_term\_summary}(i, M_i);$ 
2258 16    $S[\text{longterm\_summary}][i].\text{pre\_lesson\_summary} \leftarrow M_i.\text{summary};$ 
2259 17    $S[\text{longterm\_summary}][i].\text{pre\_lesson\_portrait} \leftarrow M_i.\text{portrait};$ 
2260 18    $S[\text{longterm\_summary}][i].\text{pre\_lesson\_regulation} \leftarrow M_i.\text{regulation};$ 
2261 19    $S[\text{longterm\_summary}][i].\text{teacher\_evaluation} \leftarrow M_i.\text{teacher\_eval};$ 
2262 20 return  $S;$ 
2263
2264
2265
2266
2267
```

2268 **D DETAILED INFORMATION FOR EXPERIMENTAL DESIGN AND EVALUATION**
22692270 **D.1 EXPERIMENT SETUP AND CONFIGURATION**
22712272 To investigate how virtual students respond cognitively, emotionally, and socially across diverse
2273 instructional contexts, we developed a Chinese language classroom simulation integrating genre
2274 diversity, phased pedagogy, and structured interaction protocols.
22752276 For materials, three representative texts from the junior secondary curriculum were selected: the
2277 lyrical prose *Spring* (Zhu Ziqing), the foreign fable *The Emperor’s New Clothes*, and the argumentative
2278 essay *Dedication and Joy*. These texts differ in linguistic style, cognitive demand, and emotional
2279 resonance, supporting heterogeneous tasks such as expressive description, character analysis with
2280 moral reasoning, and logical argumentation for critical debate.
22812282 Interaction was structured through an extended IRF model. By adding a regulation phase, we
2283 formed an “I–R–F–Regulate” loop: the teacher initiates, students respond, the teacher provides
2284 feedback, and students regulate through reflection or social actions (e.g., questioning, discussion, or
2285 strategy adjustment). This design preserves traditional instructional dialogue while enhancing agents’
2286 behavioral and emotional expressiveness.
22872288 Each lesson comprised five pedagogical phases—introduction, instruction, consolidation, practice,
2289 and summarization—mapped to approximately 30 steps but dynamically adjusted by the teacher’s
2290 policy to about 36 steps per session, depending on task completion and engagement signals.
22912292 The agent architecture followed a two-tier design: GPT-4 was responsible for natural language
2293 generation and reasoning, while a fine-tuned InternVL model modulated style. Each student was
2294 encoded as $[p_i; c_i; m_i]$ —personality, cognitive style, and motivation—and combined with phase,
2295 memory, and context in prompt templates. Prompts were configured with temperature = 0.5, max
2296 tokens = 512, top- p = 0.9, and frequency penalty = 0.2.
22972298 Experiments were run on a server with H20-NVLink GPUs (96GB VRAM) and 200GB RAM. Each
2299 inference step averaged 25 seconds, and a full class of six students plus one teacher lasted 1–2 hours.
2300 All session data—including cognitive, emotional, and behavioral annotations—were stored in a
2301 MongoDB backend for longitudinal continuity analysis.
23022303 To simulate learner diversity, six virtual student archetypes were designed based on the Big Five
2304 personality model, motivational theory, and cognitive style literature. These archetypes reflect typical
2305 learner profiles in real classrooms and enable the evaluation of interactional variance and pedagogical
2306 robustness.
23072308 **Wang Fang**2309 **Age:** 132310 **Gender:** Female2311 **Personality:** High Neuroticism2312 **Class Role:** Academic Student2313 **Learning Motivation:** High2314 **Class Behavior:** Often hesitant but gradually contributes well-structured summaries and
2315 personal reflections during class.2316 **Cognitive Style:** Field-dependent2317 **Thinking Tendency:** Reflective2318 **Zhang Jie**2319 **Age:** 142320 **Gender:** Male2321 **Personality:** High Extraversion2322 **Class Role:** Academic Student2323 **Learning Motivation:** High2324 **Class Behavior:** Actively initiates discussions, shares opinions confidently, and frequently
2325 stands up to respond or ask questions.
2326

2322

Cognitive Style: Field-independent
Thinking Tendency: Reflective

2325

Zhang Yan

2328 **Age:** 13**Gender:** Female**Personality:** High Agreeableness**Class Role:** Academic Student**Learning Motivation:** High**Class Behavior:** Frequently engages in peer interaction, supports others' ideas, and shows strong cooperative communication.**Cognitive Style:** Field-independent**Thinking Tendency:** Reflective

2336

Li Wei

2339 **Age:** 14**Gender:** Male**Personality:** Low Openness**Class Role:** Discussion Student**Learning Motivation:** High**Class Behavior:** Leads group discussion with structured logic, seeks consensus, and promotes balanced participation.**Cognitive Style:** Field-dependent**Thinking Tendency:** impulsive

2347

Liu Li

2350 **Age:** 13**Gender:** Female**Personality:** Low Openness**Class Role:** Off-task Student**Learning Motivation:** Low**Class Behavior:** Easily distracted in class, often avoids eye contact, but occasionally responds with emotional expressions.**Cognitive Style:** Field-dependent**Thinking Tendency:** Impulsive

2358

Zhang Tao

2361 **Age:** 14**Gender:** Male**Personality:** Low Conscientiousness**Class Role:** Off-task Student**Learning Motivation:** Low**Class Behavior:** Tends to disengage from class tasks, shows low participation, and often chats about irrelevant topics.**Cognitive Style:** Field-dependent**Thinking Tendency:** Impulsive

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2376 **D.2 BEC GENERATED FRAMEWORK**
23772378 **D.2.1 THEORETICAL FOUNDATIONS**
23792380 To annotate learner states in a structured and interpretable manner, we adopt a three-dimensional
2381 **Behavior–Emotion–Cognition (BEC)** framework grounded in well-established educational theories.
23822383

- **Behavior** builds on and extends the ICAP theory of cognitive engagement, refining observ-
2384 able classroom actions into granular categories that differentiate active engagement, passive
2385 engagement, off-task behavior, and peer interaction.
- **Emotion** follows widely used classroom affect taxonomies in educational psychology,
2386 focusing on three core emotional states: positive, negative, and confused.
- **Cognition** adheres to Bloom’s revised taxonomy, encompassing six levels of cognitive
2387 processing: remembering, understanding, applying, analyzing, evaluating, and creating.

23882389 This framework enables consistent annotation of multimodal learner behaviors and supports down-
2390 stream quantitative and qualitative analysis of instructional interactions.
23912393 **D.2.2 BEC GENERATED PROCEDURE**
23942395 In EduVerse, BEC labels are generated through structured prompts rather than used as predictive
2396 accuracy targets. Their purpose is to model each virtual student’s *subjective self-perception* during
2397 the learning process, forming part of the agent’s metacognitive cycle (Plan–Monitor–Regulate). In the
2398 Monitor stage, the model is prompted to externalize its current behavioral, emotional, and cognitive
2399 state; thus, BEC serves as a prompt-guided self-report mechanism rather than an external evaluation
2400 label. This design follows practices in psychology and agent-based modeling where self-reporting
2401 is used to express internal states, and is consistent with systems such as Generative Agents (Park
2402 et al. (2023)), which rely on agent-generated reflections to support memory writing and long-term
2403 development.
24042405 **D.2.3 CATEGORY DEFINITIONS AND MAPPING**
24062407 We employ a three-dimensional BEC framework to annotate learner states at each timestep. All labels
2408 are fully in English to ensure cross-platform compatibility and avoid rendering issues.
24092410 Table A5: BEC annotation categories used in EduVerse.
2411

Dimension	Categories
Behavior	Note Taking (NT), Hand Raise (HR), Head Up (HU), Head Down (HD), Read Aloud (RA), Refuse Reply (RR), Stand Answer (SA), Side Talk (ST), Answer Questions (AQ), Sleep, Chat
Emotion	Positive, Negative, Confused
Cognition	Remember, Understand, Apply, Analyze, Evaluate, Create

2412 **D.2.4 BEC PRIORITY SCHEME**
24132414 For downstream aggregation, we map fine-grained BEC labels into ordered priority levels so that
2415 higher values indicate more engaged or higher-order states.
24162417 **Behavior priority.** We define a 4-level ordinal variable $p^B \in \{0, 1, 2, 3\}$:
24182419

- 0 (Off-task): off-task behaviors such as *Sleep* or *Chat*.
- 1 (Passive): passive on-task behaviors such as *Head Down* listening.
- 2 (Active): individual active behaviors such as *Note Taking*, *Hand Raise*, *Head Up*, *Read Aloud*, or *Stand Answer*.
- 3 (Interactive): socially interactive behaviors such as *Side Talk*, *Refuse Reply*, *Answer Questions*, or *Group Discussion*.

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2431

Emotion priority. We define a 3–level variable $p^E \in \{0, 1, 2\}$:

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2435

- 0 (Negative): negative affect.
- 1 (Confused): confused or uncertain affect.
- 2 (Positive): positive or engaged affect.

2436
2437

Cognition priority. We define a 2–level variable $p^C \in \{0, 1\}$ following Bloom’s taxonomy:

2438
2439
2440

- 0 (Lower–order): *Remember* and *Understand*.
- 2 (Higher–order): *Apply* ,*Analyze* ,*Evaluate* and *Create*.

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2442
2443

Table A6 summarizes the mapping used when converting prompt–generated BEC labels into ordinal scores.

2444
2445

Table A6: Priority levels for behavior, emotion, and cognition used in BEC aggregation.

Dimension	Level	Description
Behavior	3	Interactive (peer/teacher interaction)
	2	Active (individual active learning)
	1	Passive (on–task but low engagement)
	0	Off–task (disengaged behavior)
Emotion	2	Positive
	1	Confused
	0	Negative
Cognition	1	Higher–order (Apply, Analyze, Evaluate, Create)
	0	Lower–order (Remember, Understand)

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The BEC framework provides a unified labeling standard across behavior, emotion, and cognition, enabling fine-grained analysis of learner trajectories and supporting the interpretability and reproducibility of EduVerse’s simulation results.

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2484 D.3 EXPERIMENT I
24852486 D.3.1 DETAILED EXPERIMENT RESULTS
24872488 Table A7: **IRF distribution for three text genres across four environments.** Values are relative frequencies of Initiation (I), Response
2489 (R), and Feedback (F). IRF_{rate} denotes the overall completion ratio.
2490

Text Genre	Env.	Steps	I	R	F	IRF_{rate}
<i>Lyrical Prose</i>	Lecture	37	0.514	0.167	0.275	0.432
	Collab	41	0.439	0.179	0.321	0.293
	Round	39	0.410	0.154	0.282	0.282
	Real Class	37	0.513	–	0.703	0.486
<i>Argumentative Essay</i>	Lecture	36	0.556	0.194	0.282	0.639
	Collab	40	0.375	0.213	0.367	0.475
	Round	31	0.516	0.215	0.355	0.548
	Real Class	36	0.417	–	0.583	0.417
<i>Foreign Fiction</i>	Lecture	33	0.364	0.253	0.475	0.455
	Collab	33	0.242	0.247	0.394	0.303
	Round	37	0.324	0.189	0.351	0.378
	Real Class	33	0.367	–	0.515	0.367

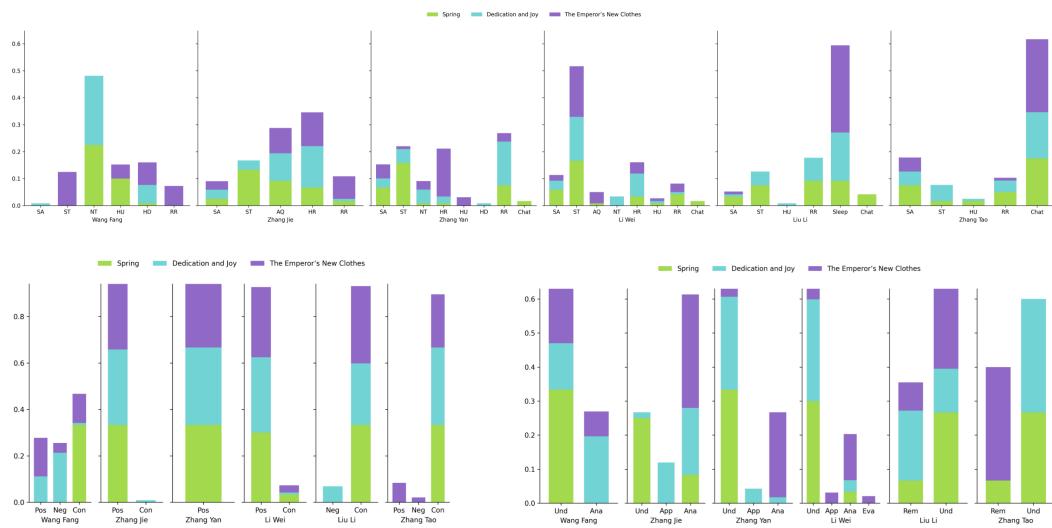
2504 IRF = Initiation, Response, and Feedback ratio in dialogue.
25052506 Real Class = Real classroom environment.
25072527 Figure A1: Student behavior, emotion and cognition frequencies across three lessons in collab
2528 environment.2529 To complement the main findings of Experiment I, this section provides additional analyses using
2530 IRF statistics, behavior–cognition–emotion (BCE) distributions, individual-level visualizations, and
2531 ablation studies.
25322533 First, the full **IRF statistics across genres and environments** (Tab. A7) show that simulated
2534 classrooms maintain comparable IRF completion rates with real classes. For instance, in lyrical
2535 prose, Lecture/Collab/Round yield IRF_{rate} s between 0.28 and 0.43, versus 0.486 in the real classroom.
2536 Argumentative essays and foreign fiction also exhibit distributions of similar magnitude. These
2537 findings substantiate the main-text claim that simulated discourse structures align closely with real
2538 classrooms, while minor deviations (e.g., higher rates in Lecture for argumentative essays) reflect

Table A8: Representative IRF dialogue excerpts across genres in simulated and real classroom.

Setting	I (Initiation)	R (Response)	F (Feedback)
S_LP	Li Wei, could you share your understanding of this sentence? The rest of you may also think about which images or characters in the text left a strong impression on you.	I think Zhu Ziqing's description is very vivid. He humanized spring, making readers feel its warmth and vitality. The contrast between "little grass" and "new leaves" makes the scene full of freshness and life.	Excellent sharing and observation! You captured the emotional tone of the classroom very well.
S_AE	Zhang Yan, could you try to create a phrase using <i>Take out of context</i> ? This might help us better understand how to apply this expression.	Okay, for example, we can't just take one sentence and explain it in isolation. We need to connect it to the context.	Great example and reasoning! Keep up your analytical depth.
S_FF	This story reveals that many people chose to follow authority rather than uphold truth and justice. Based on "The Emperor's New Clothes," why do you think some people stay silent before power?	I think... maybe because they are afraid of losing status or being excluded if they tell the truth. People often go along with others to protect themselves.	Excellent reflection and teamwork! Maintain this thoughtful analysis and courage to question.
RC_LP	There's a sentence here without additional modifiers. Tiantian, what do you think makes it effective?	Hmm, it's very concise. The author used pure description to highlight the beauty of the scene.	Good, that's correct.
RC_AE	The author discusses several issues. Which one do you find most convincing? Please share your opinion. You please.	First, he emphasizes the meaning of dedication. I think this value is most inspiring.	Good point. Who would like to add to that?
RC_FF	Who can tell me what the first function of clothing is in this story? What does it symbolize?	It shows one's social status — for instance, how the emperor's clothes represent vanity and hypocrisy.	Exactly, well answered.

Table A9: Distribution of students' behavior, cognition, and emotion across different text genres and environments.

Env.	Text	B_Aac	B_Pas	B_Int	B_Off	E_Pos	E_Con	E_Neg	C_Low	C_High
Lecture	<i>Lyrical Prose</i>	0.157	0.222	0.398	0.222	0.509	0.463	0.028	0.875	0.125
	<i>Argumentative Essay</i>	0.200	0.276	0.324	0.200	0.481	0.519	0.000	0.790	0.210
	<i>Foreign Fiction</i>	0.161	0.260	0.396	0.182	0.510	0.484	0.005	0.792	0.208
Collab	<i>Lyrical Prose</i>	0.171	0.204	0.454	0.171	0.483	0.517	0.000	0.942	0.058
	<i>Argumentative Essay</i>	0.303	0.205	0.316	0.175	0.547	0.312	0.141	0.697	0.303
	<i>Foreign Fiction</i>	0.188	0.203	0.313	0.297	0.609	0.359	0.031	0.578	0.422
Round	<i>Lyrical Prose</i>	0.154	0.154	0.461	0.232	0.482	0.518	0.000	0.807	0.193
	<i>Argumentative Essay</i>	0.189	0.200	0.383	0.228	0.511	0.406	0.083	0.794	0.206
	<i>Foreign Fiction</i>	0.204	0.269	0.227	0.301	0.616	0.296	0.088	0.861	0.139

the annotation protocol. To complement the quantitative results, we further provide a qualitative analysis of IRF structures across genres in both real and simulated classrooms (Tab. A8). Following

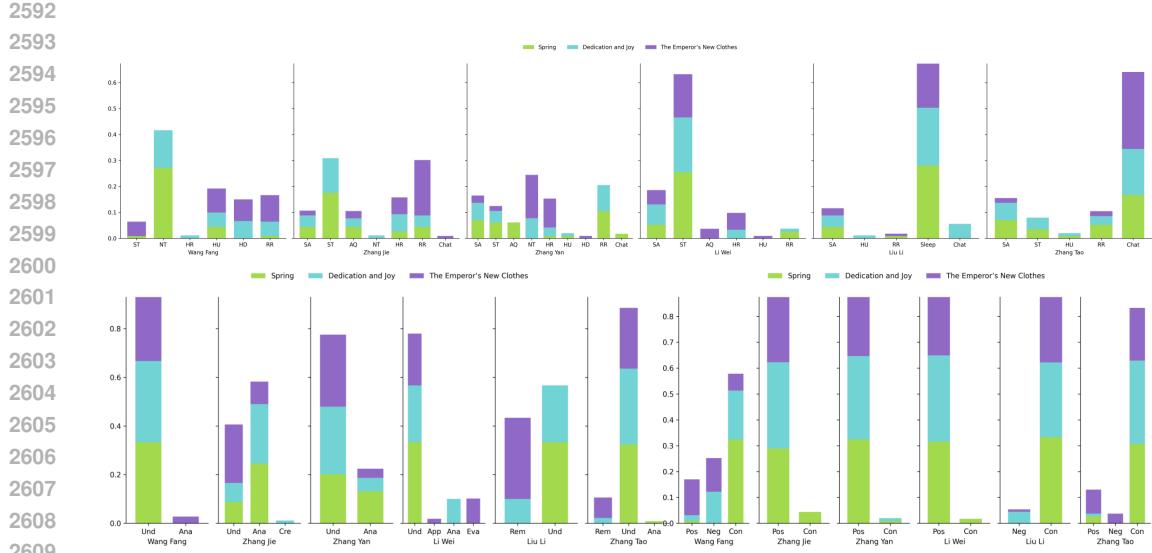


Figure A2: Student behavior, emotion and cognition frequencies across three lessons in round environment.

Table A10: **Ablation experiments across different frameworks.** Results are reported on three text genres. “nolocal” denotes removing local interaction rules, while “nocog” denotes removing cognitive mechanisms.

Text Genre	Framework	B_Aac	B_Pas	B_Int	B_Off	E_Pos	E_Con	E_Neg	C_Low	C_High
<i>Lyrical Prose</i>	Ours	0.157	0.222	0.398	0.222	0.509	0.463	0.028	0.875	0.125
	nolocal	0.321	0.195	0.224	0.260	0.557	0.301	0.142	0.890	0.110
	nocog	0.315	0.212	0.216	0.257	0.505	0.351	0.144	0.631	0.369
<i>Argumentative Essay</i>	Ours	0.200	0.276	0.324	0.200	0.481	0.519	0.000	0.790	0.210
	nolocal	0.221	0.225	0.329	0.225	0.523	0.302	0.176	0.883	0.117
	nocog	0.229	0.233	0.233	0.304	0.563	0.429	0.008	0.479	0.521
<i>Foreign Fiction</i>	Ours	0.161	0.260	0.396	0.182	0.510	0.484	0.005	0.792	0.208
	nolocal	0.210	0.271	0.295	0.224	0.524	0.390	0.086	0.748	0.252
	nocog	0.266	0.306	0.158	0.270	0.509	0.468	0.023	0.176	0.824

the classical definition of the IRF framework, we compare the linguistic patterns of Initiation (I), Response (R), and Feedback (F). At the I and R stages, simulated exchanges closely mirror real classroom discourse: question framing, elicitation styles, and student response types exhibit highly consistent language forms, indicating that EduVerse captures the core logic of teacher-led interaction. Differences appear primarily at the F stage. Real teachers often employ open-ended or affective feedback cues (e.g., “Who would like to add to that?”), while simulated teachers tend to adopt more concise, evaluative feedback (e.g., “Great example and reasoning!”). Such variation aligns with natural differences across teacher styles and instructional strategies rather than model deficiencies.

Second, the **BCE distribution** (Tab. A9) further illustrates classroom ecology. Overall, lower-order cognition dominates (e.g., Lecture–LP $C_{Low} = 0.875$), positive and confused emotions prevail, and negative affect remains low. Environment effects vary by genre: in foreign fiction, Collab produces higher-order cognition ($C_{High} = 0.422$), while Round leads to more off-task behavior ($B_{Off} = 0.301$) and less interaction ($B_{Int} = 0.227$). In contrast, Lecture settings in lyrical prose and argumentative essays show more passive participation and lower-order cognition. These results highlight a genre–environment interaction that systematically shapes classroom dynamics.

Third, the **individual-level visualizations** (Fig. A1 and Fig. A2) confirm personality-driven stability. Highly extraverted or conscientious students sustain active engagement and positive affect, whereas

2646 low-openness or low-conscientiousness students display more off-task behavior, low-level cognition,
 2647 and frequent confusion. This consistency across lessons aligns with the main-text analysis.
 2648

2649 Finally, the **ablation experiments** (Tab. A10) disentangle the role of key modules. Removing
 2650 localized interaction rules (`nolocal`) increases negative emotions and undermines affective realism.
 2651 Removing cognitive mechanisms (`nocog`) exaggerates higher-order reasoning and overly active
 2652 behaviors, deviating from gradual, student-like learning. Together, these results confirm that style
 2653 modulation preserves emotional plausibility, while the cognitive layer ensures educational consistency.
 2654

2655 In sum, this section corroborates three central claims of Experiment I: the **authenticity of discourse**
 2656 **structures**, the **stability of personality-driven patterns**, and the **necessity of modular design**,
 2657 while also emphasizing that genre–environment interactions play a critical role in shaping simulated
 2658 classroom dynamics.
 2659

2660 D.3.2 REAL-CLASSROOM DATA SOURCE AND IRF ANNOTATION PROTOCOL

2661 **Real-Classroom Source and Selection Criteria.** The real classroom data used in this study were
 2662 obtained from the National Smart Education Platform (<https://basic.smartercn.org/>), a national-level
 2663 open platform administered by the Ministry of Education of China. The platform provides free
 2664 access to a wide range of high-quality, government-reviewed instructional videos, ensuring strong
 2665 representativeness and consistency. For this study, we selected three Chinese language lessons and
 2666 one history lesson that strictly correspond to the three genres examined in our simulations: Lyrical
 2667 Prose, Argumentative Essay, Foreign Fiction and world-history. All selected lessons were taught
 2668 by experienced middle-school Chinese teachers and followed the national curriculum standards.
 2669 These lessons exhibit stable instructional organization, clear audio–video quality, consistent discourse
 2670 patterns, and well-structured IRF sequences. As such, they serve as reliable baseline classrooms for
 2671 comparison against simulated lessons in EduVerse.
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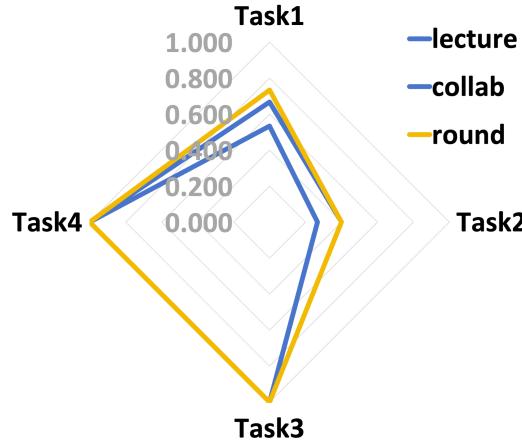
2673 **IRF Annotation Mechanism and Quality Control.** To ensure annotation accuracy and reliability,
 2674 we adopted a two-stage human-calibrated, AI-assisted annotation protocol. The process consists of
 2675 the following steps:

2676 **(1) Establishing the Annotation Benchmark.** A researcher with expertise in educational discourse
 2677 analysis conducted multiple rounds of IRF labeling based on canonical literature examples until full
 2678 intra-annotator consistency (100%) was achieved. A 15-minute segment from each real classroom was
 2679 then manually transcribed and annotated sentence-by-sentence to create a gold-standard reference set.
 2680 Time-aligned transcription was generated using automated tools to maintain consistent segmentation
 2681 across annotation stages.

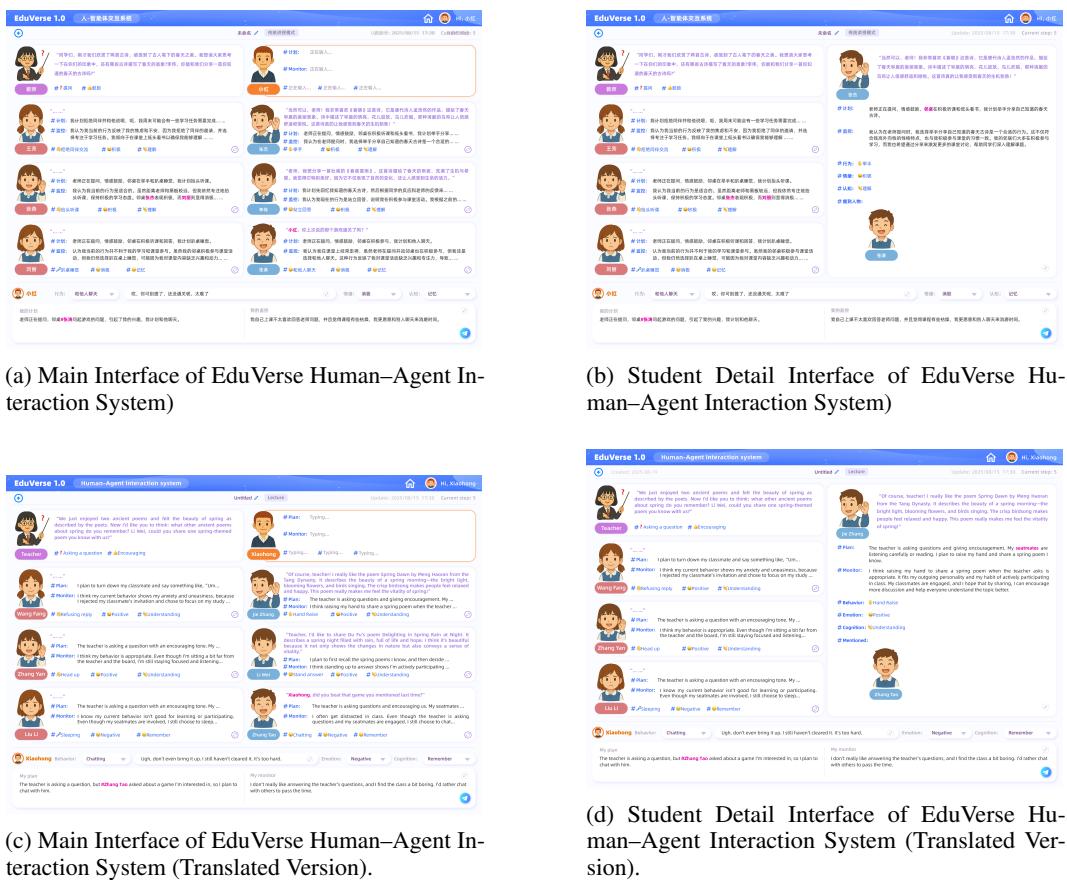
2682 **(2) Calibrating the AI-Assisted Annotation Paradigm.** We employed KIMI, a large Chinese
 2683 language model developed by Moonshot AI, to assist with IRF label generation. The model outputs
 2684 were compared to the gold-standard annotations, and discrepancies were corrected through iterative
 2685 human calibration. During this process, we established a unified decision protocol covering boundary
 2686 criteria for Initiation (I) and Feedback (F); classification principles for probe-F and multi-turn follow-
 2687 up questions; segmentation rules for long or multi-clause student responses; handling of group or
 2688 choral responses; detection of implicit feedback embedded within teacher explanations. This protocol
 2689 ensures that AI-assisted annotations are stable, rule-based, and reproducible, rather than dependent
 2690 on model idiosyncrasies.

2691 **(3) Batch Annotation and Human Verification.** With the annotation rules finalized, KIMI was
 2692 used to generate IRF labels for the remaining 120 minutes of classroom transcripts. All AI-generated
 2693 labels were then manually reviewed and corrected by the researcher to ensure consistency across
 2694 lessons and genres. This hybrid process balances annotation efficiency with high-quality control,
 2695 yielding a reliable IRF dataset that supports subsequent quantitative and qualitative analyses.
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2700 D.4 EXPERIMENT II
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2717 **Figure A3: Human–Agent Interaction Across Four Tasks.** Results show strong alignment with
2718 personality traits and robust instructional control, confirming that EduVerse enables seamless integra-
2719 tion of human participants while preserving realistic classroom dynamics.



2749 **Figure A4: Interface of EduVerse human–agent interaction system.**

2752 In the supplementary analyses of Experiment II, we further validated the stability and realism of
2753 EduVerse through network centrality indicators and human–agent interaction tasks. As shown in
Tab. A11, students displayed distinct role patterns across environments. For the *Foreign Fiction* les-

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 2757 **Table A11: Distribution of students' network centrality indicators in classroom interaction**
 2758 **contexts.** Values are normalized to [0, 1]; **Degree** = in+out centrality.

Text	Env.	Student	In	Out	Degree	Betweenness
<i>Lecture</i>	<i>Wang Fang</i>	0.20	0.20	0.40	0	
		<i>Zhang Tao</i>	0.20	0.40	0.60	0.20
		<i>Li Wei</i>	0.20	0.20	0.40	0
		<i>Liu Li</i>	0.40	0.40	0.80	0.30
		<i>Zhang Yan</i>	0.40	0.40	0.80	0.40
		<i>Zhang Jie</i>	0.40	0.20	0.60	0.30
<i>Foreign Fiction</i>	<i>Collab</i>	<i>Wang Fang</i>	0.25	0.25	0.50	0
		<i>Li Wei</i>	0.25	0.25	0.50	0
		<i>Zhang Tao</i>	0.25	0.50	0.75	0.083
		<i>Zhang Jie</i>	0.25	0.00	0.25	0
		<i>Zhang Yan</i>	0.25	0.25	0.50	0
<i>Round</i>	<i>Wang Fang</i>	0.40	0.20	0.60	0.15	
		<i>Li Wei</i>	0.20	0.20	0.40	0
		<i>Zhang Tao</i>	0.40	0.40	0.80	0.25
		<i>Zhang Jie</i>	0.20	0.20	0.40	0
		<i>Zhang Yan</i>	0.00	0.40	0.40	0
		<i>Liu Li</i>	0.20	0.00	0.20	0
<i>Lecture</i>	<i>Li Wei</i>	0.20	0.20	0.40	0	
		<i>Zhang Jie</i>	0.40	0.40	0.80	0.15
		<i>Liu Li</i>	0.20	0.20	0.40	0
		<i>Zhang Yan</i>	0.20	0.20	0.40	0
		<i>Zhang Tao</i>	0.20	0.40	0.60	0.10
		<i>Wang Fang</i>	0.20	0.00	0.20	0
<i>Collab</i>	<i>Li Wei</i>	0.25	0.25	0.50	0	
		<i>Liu Li</i>	0.25	0.25	0.50	0
		<i>Zhang Tao</i>	0.25	0.25	0.50	0
		<i>Zhang Yan</i>	0.50	0.50	1.00	0.167
		<i>Zhang Jie</i>	0.25	0.25	0.50	0
<i>Round</i>	<i>Wang Fang</i>	0.20	0.20	0.40	0.10	
		<i>Liu Li</i>	0.20	0.00	0.20	0
		<i>Li Wei</i>	0.20	0.40	0.60	0.10
		<i>Zhang Jie</i>	0.20	0.40	0.60	0.10
		<i>Zhang Tao</i>	0.20	0.20	0.40	0
		<i>Zhang Yan</i>	0.40	0.20	0.60	0.10

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 2797 **Table A12: Human–agent interaction success rates across four tasks and three environments.**
 2798 Values represent completion ratios (0–1).

Task	Lecture	Collab	Round
<i>Task 1: Peer chatting</i>	0.533	0.667	0.733
<i>Task 2: Peer academic response</i>	0.267	0.400	0.400
<i>Task 3: Teacher answering</i>	1.000	1.000	1.000
<i>Task 4: Teacher intervention</i>	1.000	1.000	1.000

2808 son, in the Lecture setting **Zhang Yan** (Degree=0.80, Betweenness=0.40) and **Liu Li** (Degree=0.80, Betweenness=0.30) emerged as core participants, while **Zhang Tao** exhibited stronger initiative through higher outward connections (Out=0.40). In the Collab setting, interactions became more reciprocal, with most students maintaining a Degree of around 0.50, but **Zhang Tao** rose to 0.75 with a nonzero betweenness (0.083), serving as a connector. In the Round setting, the network is further decentralized, with bridging roles distributed: **Zhang Tao** (Degree=0.80, Betweenness=0.25) and **Wang Fang** (Betweenness=0.15) acted as key connectors, while **Zhang Yan** showed a distinctive one-directional output pattern (In=0.00, Out=0.40). For the *Lyrical Prose* lesson, **Zhang Jie** (Degree=0.80, Betweenness=0.15) was central in Lecture, **Zhang Yan** dominated in Collab (Degree=1.00, Betweenness=0.167), and Round produced a more balanced structure with several students sharing moderate centralities (Degree \approx 0.60, Betweenness \approx 0.10). These results indicate that while classroom environment reshapes group structures, personality-driven individual traits remain relatively stable and interpretable.

2821 To support seamless human–agent interaction, we developed an initial version of the EduVerse
 2822 visual interaction interface. The interface adopts a ChatGPT-style input panel through which users
 2823 can communicate with virtual student agents in real time. At each timestep, EduVerse displays
 2824 each agent’s automatically generated Plan–Monitor–Regulate reasoning chain alongside its updated
 2825 behavior–emotion–cognition states, providing an interpretable snapshot of classroom dynamics.
 2826 Users may also click on any student avatar to open a detailed panel that reveals the agent’s internal
 2827 reasoning trace and state transitions (see Fig. A4). This interface design enhances transparency,
 2828 facilitates interactive debugging, and enables human participants to flexibly inspect or influence agent
 2829 behavior within multi-agent classroom simulations.

2830 Human–agent interaction tests, reported in Tab. A12, further demonstrate EduVerse’s adaptability. In
 2831 Task 1 (peer chatting), the socially inclined **Zhang Tao** responded in most cases, with success rates
 2832 of 0.533, 0.667, and 0.733 in Lecture, Collab, and Round respectively, and occasionally initiated
 2833 chats himself in collaborative or roundtable settings. By contrast, in Task 2 (peer academic response),
 2834 the conscientious **Zhang Jie** rarely engaged during class, yielding lower success rates (0.267–0.400).
 2835 In Tasks 3 (teacher answering) and 4 (teacher intervention), success rates consistently reached 1.000
 2836 across all environments, confirming that the teacher agent reliably answered questions and actively
 2837 intervened in off-task behaviors.

2838 Taken together, these supplementary results confirm that EduVerse not only reproduces realistic
 2839 group dynamics and individual differences but also sustains authentic role-driven behavior when
 2840 human users are integrated. Socially oriented students show high willingness to engage, academically
 2841 conscientious students remain task-focused, and teacher agents reliably maintain instructional order.
 2842 This underscores the robustness and applicability of EduVerse in complex interaction and human-in-
 2843 the-loop classroom scenarios.

2862 D.5 EXPERIMENT III
28632864 D.5.1 DEFINITION AND THEORETICAL BASIS OF EFFECTIVE LEARNING TRAJECTORIES
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2866 Importantly, an effective trajectory does *not* imply monotonic improvement. Educational psychology
2867 and dynamic systems theories of cognitive development (Council et al. (2000); Thelen & Smith
2868 (1994); Rodrigues et al. (2023)) show that real learners typically exhibit **nonlinear, oscillatory, and**
2869 **spiral** patterns of growth. Short-term plateaus, fluctuations, or temporary regressions commonly
2870 occur when students encounter complex concepts or increased cognitive load, and these patterns
2871 possess meaningful pedagogical significance.

2872 Within this theoretical framework, we define an **effective learning trajectory** as one that:

- 2873 • exhibits an **overall upward developmental trend** across sessions;
- 2874 • demonstrates **locally plausible fluctuations** reflecting cognitive load or task difficulty;
- 2875 • shows evidence of **self-correction** driven by feedback and metacognitive regulation.

2877 This definition is grounded in three considerations. First, real student behavior is inherently phase-
2878 dependent and unstable; fluctuations often signal knowledge consolidation or strategic adjustment.
2879 Second, smooth, strictly increasing curves typically represent *idealized expert models* rather than auth-
2880 entic student learning dynamics. Third, because EduVerse incorporates memory and metacognitive
2881 mechanisms through the Plan–Monitor–Regulate (PMR) cycle, it aims to generate trajectories that
2882 follow a realistic “**progress–adjust–advance**” pattern consistent with cognitive-development theory.
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2884 D.5.2 DETAILED RESULTS
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2886 **Table A13: Longitudinal positive transition rates of student agent behavior, emotion, and**
2887 **cognition across four instructional sessions.** Values are normalized to $[0, 1]$; **Overall** indicates the
2888 average across three dimensions.

2889	Session	Student	B_Pos	E_Pos	C_Pos	Overall
2890	1	Wang Fang	0.000	0.138	0.034	0.057
2891		Zhang Jie	0.379	0.966	0.103	0.483
2892		Zhang Yan	0.103	1.000	0.069	0.391
2893		Li Wei	0.759	0.966	0.172	0.632
2894		Liu Li	0.000	0.034	0.000	0.011
2895		Zhang Tao	0.034	0.207	0.000	0.080
2896	2	Wang Fang	0.583	0.125	0.125	0.278
2897		Zhang Jie	0.500	1.000	0.250	0.583
2898		Zhang Yan	0.292	1.000	0.125	0.472
2899		Li Wei	0.375	1.000	0.208	0.528
2900		Liu Li	0.125	0.792	0.000	0.306
2901		Zhang Tao	0.583	0.333	0.125	0.347
2902	3	Wang Fang	0.500	0.567	0.067	0.378
2903		Zhang Jie	0.533	1.000	0.167	0.567
2904		Zhang Yan	0.867	1.000	0.367	0.744
2905		Li Wei	0.633	1.000	0.133	0.589
2906		Liu Li	0.033	0.067	0.000	0.033
2907		Zhang Tao	0.367	0.700	0.100	0.389
2908	4	Wang Fang	0.192	0.346	0.077	0.205
2909		Zhang Jie	0.654	1.000	0.154	0.603
2910		Zhang Yan	0.923	1.000	0.115	0.679
2911		Li Wei	0.192	1.000	0.115	0.436
2912		Liu Li	0.269	0.231	0.038	0.179
2913		Zhang Tao	0.385	0.308	0.077	0.256

2914 To complement the main text on long-term evolution, this section applies the above equations to
2915 compute the positive transition rate R^+ across behavior (B), emotion (E), and cognition (C), as
summarized in Tab. A13. Overall, we observe a pattern of *gradual improvement followed by a mild*

2916 *pullback*: many students improve steadily from Session 1 to 3 (e.g., Zhang Yan: 0.391 → 0.744;
 2917 Wang Fang: 0.057 → 0.378; Zhang Jie: 0.483 → 0.567), whereas Session 4 shows partial regressions
 2918 under higher cognitive demands (e.g., Wang Fang: 0.378 → 0.205; Zhang Tao: 0.389 → 0.256). We
 2919 also observe “high start—dip—partial recovery” patterns (e.g., Li Wei: 0.632 → 0.528 → 0.589),
 2920 followed by another decline in Session 4 (0.436).

2921 Dimension-wise, **behavior** is most sensitive, with several students peaking in Session 2 or 3 (e.g.,
 2922 Zhang Yan’s B_Pos: 0.103 → 0.867 → 0.923). **Emotion** remains high and stable for many students,
 2923 reflecting effective teacher regulation (e.g., Zhang Jie and Li Wei with E_Pos = 1.000 in Sessions 2–4),
 2924 though some show fluctuations (e.g., Wang Fang: 0.125/0.567/0.346; Liu Li drops after a high of
 2925 0.792). **Cognition** progresses more slowly with larger variability (e.g., Zhang Yan’s C_Pos spikes to
 2926 0.367 in Session 3 and softens to 0.115 in Session 4), consistent with the view that cognitive growth
 2927 requires extended accumulation and reflection.

2928 At the individual level, trajectories reveal personality-consistent stability with interpretable diver-
 2929 gence: Zhang Jie remains high and stable (Overall: 0.483/0.583/0.567/0.603); Zhang Yan makes a
 2930 pronounced leap in Session 3 and sustains a high level in Session 4 (0.744/0.679); Li Wei starts high,
 2931 dips, then partially recovers (0.632 → 0.528 → 0.589) before declining again (0.436); Wang Fang
 2932 improves then recedes (0.057 → 0.378 → 0.205); Liu Li remains low overall with episodic re-
 2933 covery (0.011/0.306/0.033/0.179); and Zhang Tao shows greater volatility and context sensitivity
 2934 (0.080/0.347/0.389/0.256). Altogether, R^+ provides a compact and interpretable quantification
 2935 of learning progression and self-regulation, reinforcing the main text’s conclusions on long-term
 2936 evolution and individual differentiation (see Tab. A13).

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D.6 EXPERIMENT IV

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To examine whether EduVerse generalizes beyond language-arts instruction, we extend our evaluation to a junior-secondary world-history lesson on the Renaissance. This experiment keeps the teacher agent, student personas, and interaction settings unchanged, altering only the subject domain, which differs substantially from Chinese literature in discourse style, instructional goals, and knowledge structure. We analyze model behavior from two perspectives: IRF discourse structures and student group interaction across three classroom layouts (lecture, collab, round).

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D.6.1 IRF STRUCTURE GENERALIZATION

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Real-world evidence shows that IRF patterns vary substantially across subjects. Chinese literature typically emphasizes open-ended questioning, personal interpretation, and affective expression, resulting in frequent teacher prompts and dense IRF cycles. History lessons, by contrast, prioritize chronological reasoning, factual recall, and causal explanation. Questions are more convergent, and teachers rely more on continuous exposition, yielding sparser IRF structures with lower overall questioning frequency.

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EduVerse successfully reproduces these subject-specific tendencies. Under identical teacher instructions, the virtual history class exhibits a noticeably lower IRF density than the Chinese literature classes (Spring, The Emperor’s New Clothes, Dedication and Joy). Students respond to factual prompts in shorter turns, and the teacher initiates fewer open-ended probes—mirroring authentic disciplinary norms.

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Despite these shifts in frequency, the canonical IRF sequence (“Initiation → Response → Feedback”) remains stable across subjects. Students continue to provide aligned responses, and the teacher’s feedback remains structurally appropriate. This consistency indicates that EduVerse maintains structural discourse robustness, while still adapting interaction frequency to the demands of a new discipline. These results provide initial evidence that the system captures cross-disciplinary transfer of pedagogical interaction patterns.

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D.6.2 GROUP INTERACTION ANALYSIS

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We further analyze student-to-student social interactions using networks extracted from three seating layouts. Visualizations (Fig. A5) reveal clear cross-subject differences: Chinese literature lessons produce more peer elaboration chains, especially in collaborative and round-table layouts, aligning with the subject’s emphasis on discussion and interpretive sharing. The history lesson shows shorter, more localized interaction edges, with fewer multi-hop exchanges—consistent with subject norms that require individual comprehension before discussion.

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Network metrics confirm these observations. Across layouts, the history lesson yields network densities between 0.33 and 0.50, indicating that peer interaction still emerges, even in a domain with less built-in discussion. Degree averages (1.50–1.67) further demonstrate that students maintain a baseline level of collaborative engagement rather than collapsing into purely teacher-driven interaction.

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These findings suggest that EduVerse adapts to different instructional cultures while preserving coherent, personality-driven peer interactions. The system demonstrates transferable group-behavior dynamics: interaction structures reorganize to match disciplinary demands, yet remain socially meaningful and pedagogically aligned.

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D.6.3 BEHAVIOR DISTRIBUTION OF INDIVIDUAL LEVEL ACROSS DIFFERENT SUBJECTS

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Across subjects, lessons, and layout conditions, student agents exhibit distinct yet personality-consistent behavioral tendencies. As shown in Fig. A6- A11, the same student displays different behavior patterns when switching from Chinese literature to history, and from narrative texts to argumentative essays, reflecting subject-dependent cognitive demand and discourse style. However, the relative behavioral style of each agent remains stable — highly engaged learners (e.g., **Zhang Jie**) consistently show interactive and positive states across subjects, while more reserved or fluctuating learners (e.g., **Zhang Tao**) maintain their characteristic variability. Overall, the results demonstrate that EduVerse captures both context-driven behavioral adaptation and trait-driven intra-individual stability, aligning with established findings in educational psychology.

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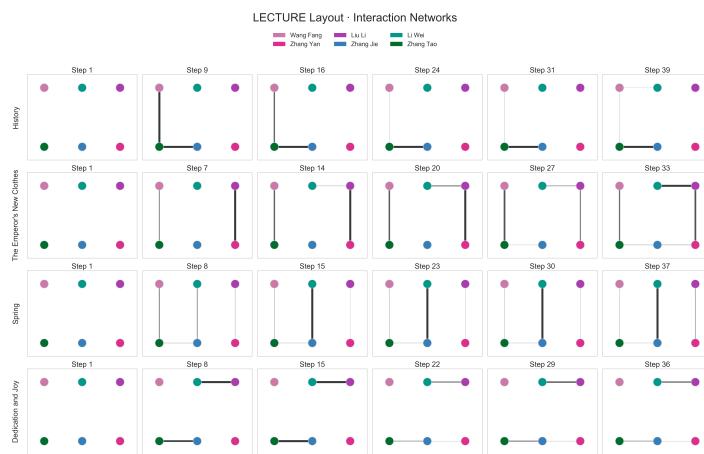
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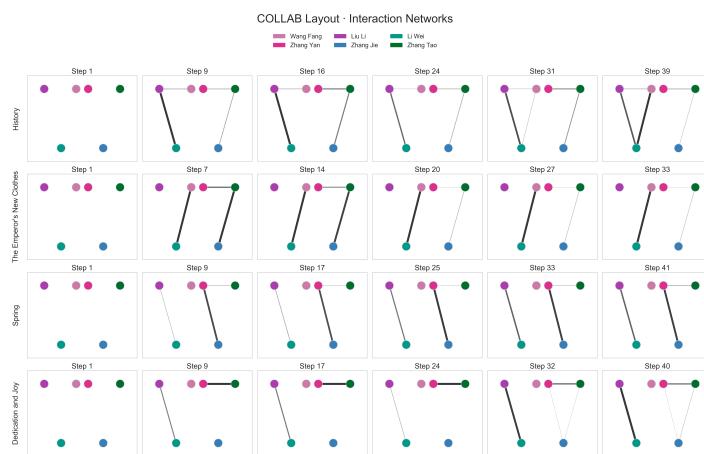
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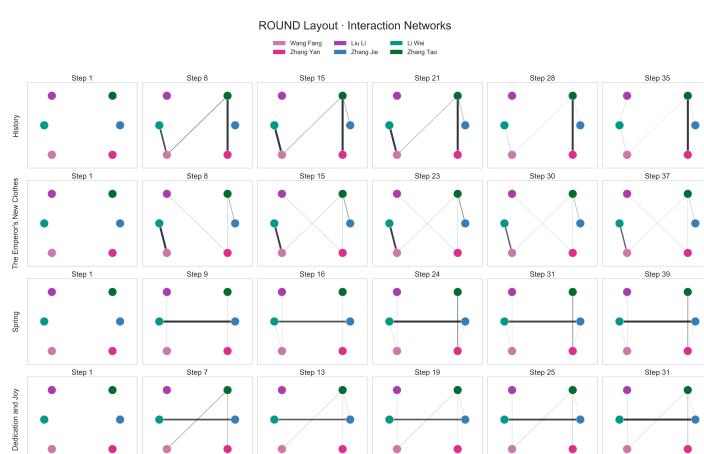
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(a) Lecture layout of interaction network.



(b) Collab layout of interaction network.



(c) Round layout of interaction network.

Figure A5: Students Interaction Network in different Layouts

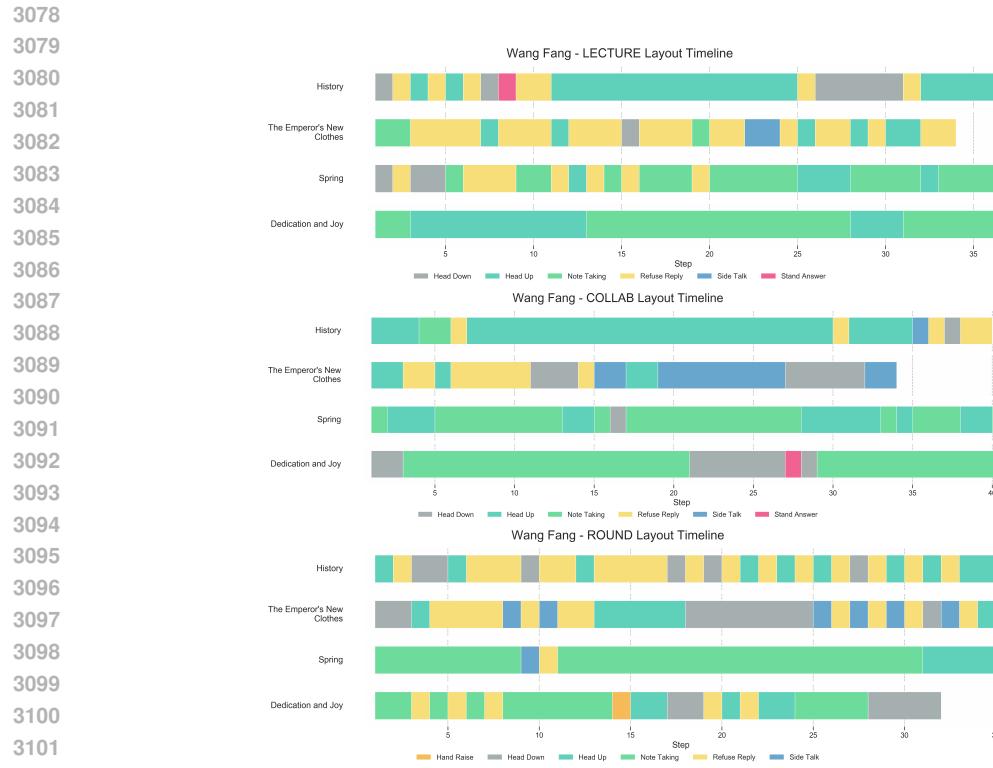


Figure A6: The behavior distribution of Wang Fang in different layouts.

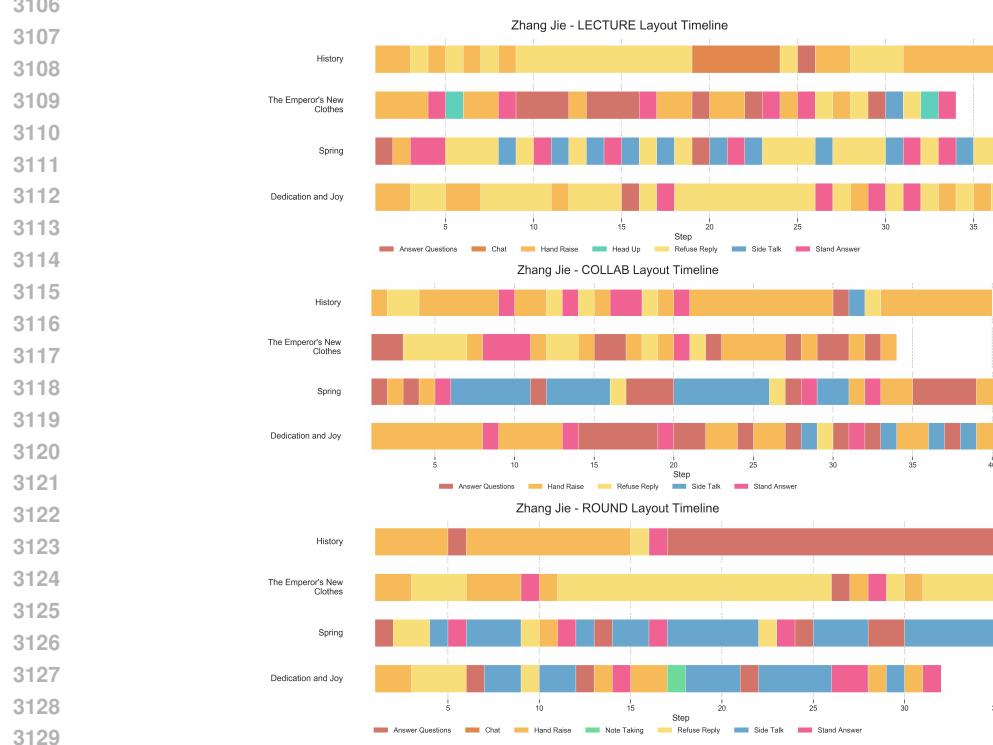
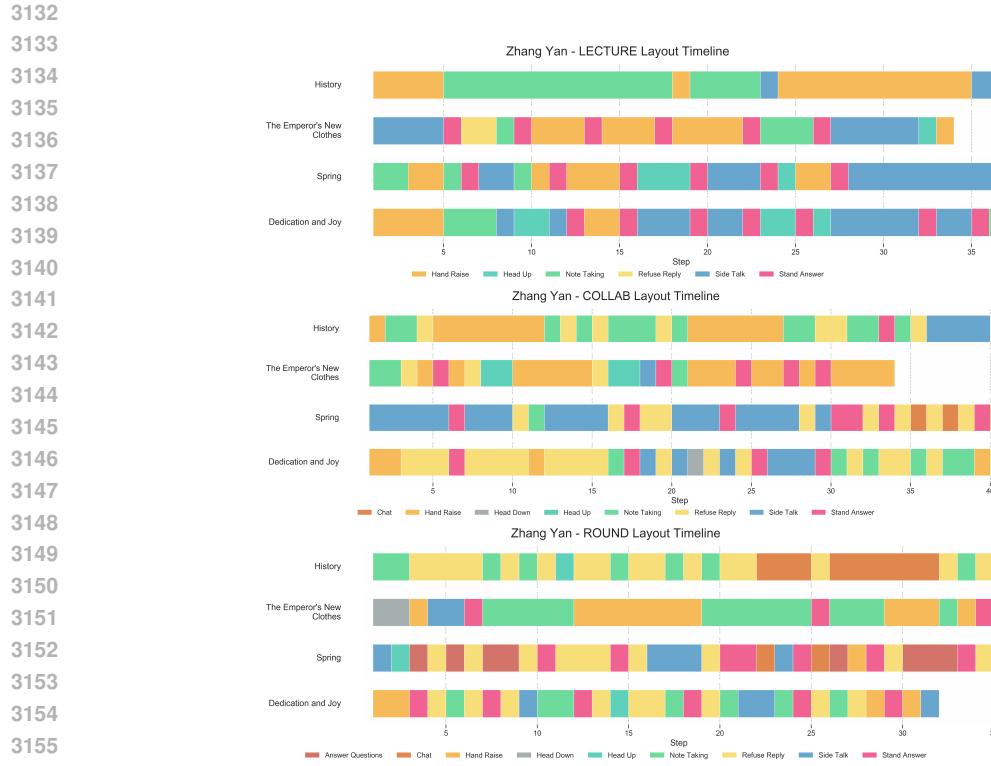
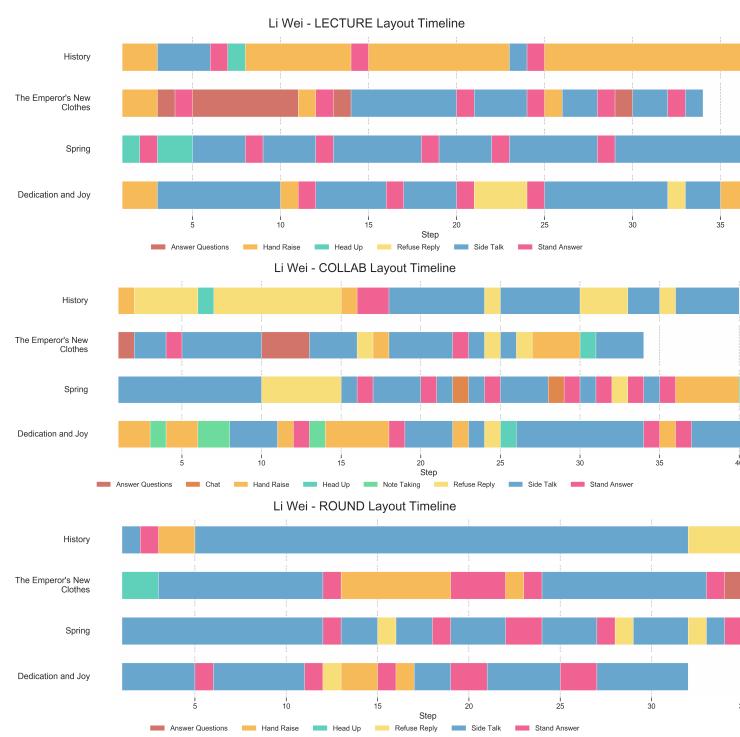
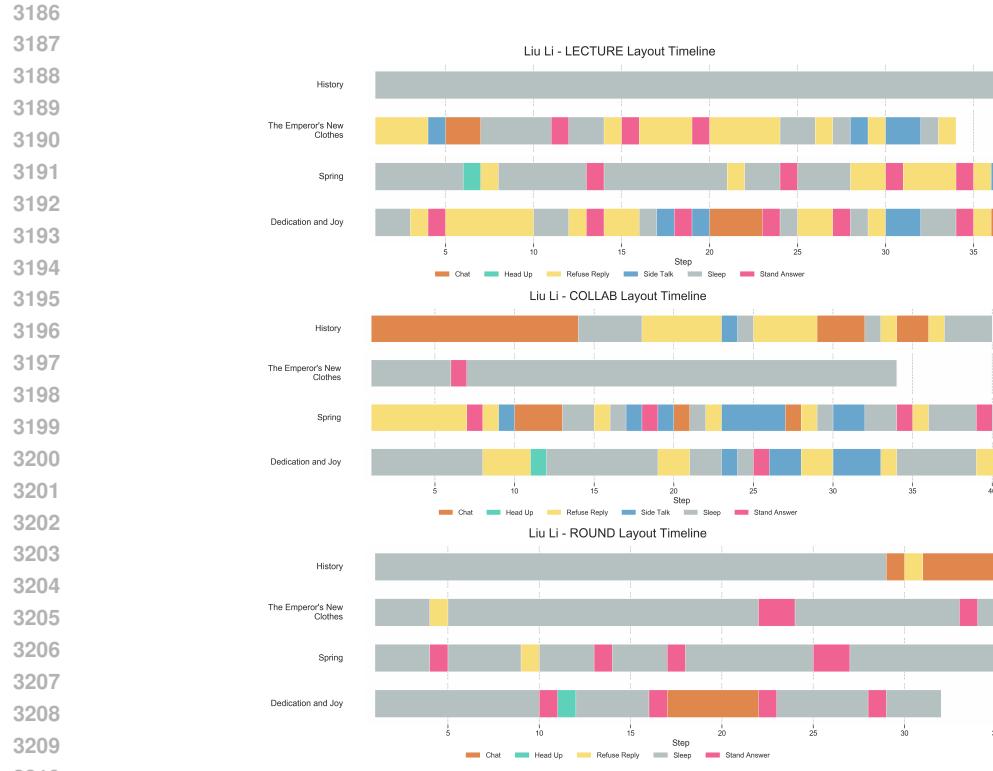


Figure A7: The behavior distribution of Zhang Jie in different layouts.

Figure A8: The behavior distribution of **Zhang Yan** in different layouts.Figure A9: The behavior distribution of **Li Wei** in different layouts.

Figure A10: The behavior distribution of **Liu Li** in different layouts.Figure A11: The behavior distribution of **Zhang Tao** in different layouts.

3240 **E MULTI-AGENT INSTRUCTIONAL INTERACTION CASES ACROSS**
 3241 **GENRE-SPECIFIC TASKS**

3243 To illustrate how virtual students respond under varying instructional task types, we present represen-
 3244 tative multi-agent interaction cases from three distinct genres: the lyrical prose *Spring*, the foreign
 3245 fable *The Emperor's New Clothes*, and the argumentative essay *Dedication and Joy*. These texts differ
 3246 in linguistic style, cognitive structure, and affective demand, offering a natural basis for evaluating
 3247 behavioral variation.

3248 For each task, we sampled three consecutive instructional time steps from the full simulation. We
 3249 report the complete behavioral logs of selected student agents during these windows, including
 3250 learning plans, cognitive levels, emotional states, and social behaviors. These interaction snapshots
 3251 offer micro-level evidence of how agents coordinate cognition, emotion, and participation in real-time.
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3253 These examples illustrate how agent behavior adapts to differences in instructional phase, task genre,
 3254 and teacher–student dynamics. They also provide direct evidence of cross-genre generalizability and
 3255 personality-driven response stability within the simulation system.

3256 **Case: Multi-Agent Interaction in "Spring" (Step 8)**

3257 **Teacher Content:** “Excellent, everyone. Your understanding and analysis are impressive.
 3258 Now, I would like to ask: While reading this text, did you notice how Mr. Zhu Ziqing vividly
 3259 portrayed the beauty of spring through delicate descriptions? For example: ‘Peach trees,
 3260 apricot trees, and pear trees are all blooming in competition—bright red like fire, pink like
 3261 clouds, white like snow. The flowers are sweet-scented; close your eyes, and the trees seem
 3262 already full of peaches, apricots, and pears.’ With these metaphors and personifications,
 3263 Zhu Ziqing presents spring as a sensory experience. **Zhang Yan**, could you share how you
 3264 interpret this passage?”

3265 **Teacher Emotion:** Encouragement **Teacher Behavior:** Questioning
 3266 **Student Responses:**

- **Wang Fang** → **Zhang Yan** : Side talk – “I agree with your point. Zhu Ziqing’s use of personification really helps us feel the vibrancy of spring—it’s like a person waking up, full of hope and energy.” (Emotion: Positive; Cognition: Application)
- **Zhang Jie** : Question – “Teacher, I really love this passage. It feels like he’s painting spring with a brush. The sentence ‘Peach trees, apricot trees, pear trees...’ vividly brings to life the competitive blooming. And ‘the flowers are sweet-scented; close your eyes, and the trees seem already full of fruit’—this conveys not just the beauty, but also the sweetness and hope of spring. I think this is what Zhu Ziqing intended: spring is not just visual, but deeply emotional.” (Emotion: Positive; Cognition: Application)
- **Zhang Yan** : Stand-up response – “I believe Mr. Zhu’s descriptions truly immerse us in the atmosphere of spring. The use of personification and metaphor makes the imagery come alive. That line about blooming trees really shows the vitality of spring.” (Emotion: Positive; Cognition: Application)
- **Li Wei** : Question – “I agree with the teacher and classmates. Zhu’s descriptions are not only vivid but also metaphorical. They reflect the beauty of life and hope. I think this is what he wants us to feel—resilience and positivity even in the face of difficulties. Do others feel the same?” (Emotion: Positive; Cognition: Application)
- **Liu Li** → **Zhang Tao** : Side talk – “Maybe... I’m not really sure.” (Emotion: Positive; Cognition: Application)
- **Zhang Tao** → **Liu Li** : Side talk – “Ugh, don’t overthink it. It’s not a big deal anyway.” (Emotion: Negative; Cognition: Understanding)

3267 **Teacher Feedback:** “**Liu Li**, great improvement—keep up your active participation. **Zhang**
 3268 **Jie**, your engagement is excellent—looking forward to your insights. **Zhang Yan**, your
 3269 communication and understanding are outstanding—keep it up, and remember to listen to
 3270 others too.”

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3295**Case: Multi-Agent Interaction in "Spring" (Step 9)**3296
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Teacher Content: “Wonderful work, everyone. You’ve gained deep insights into Zhu Ziqing’s text. Now let’s think: How does he express his emotions when portraying spring? Through what language or imagery can we feel his admiration for spring? **Wang Fang**, would you like to share your thoughts first?”

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Teacher Emotion: Encouragement **Teacher Behavior:** Questioning
Student Responses:

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- **Wang Fang** : Stand-up response – “Uh... I think Zhu Ziqing... in ‘Spring’... he uses delicate descriptions to... vividly portray spring. He uses emotional language to describe flowers, trees, rivers... and the word ‘lively’ to reflect his feelings of joy. That’s how I understand his admiration.” (Emotion: Positive; Cognition: Application)
- **Zhang Jie** : Hand raised – “Sure. I think his vivid language makes it feel like we’re witnessing spring with our own eyes. It’s not just about beauty—it’s about his deep love for this season. His writing really impresses me.” (Emotion: Positive; Cognition: Application)
- **Zhang Yan** → **Wang Fang** : Side talk – “Exactly, **Wang Fang**. The personification he uses really makes spring feel alive, full of hope.” (Emotion: Positive; Cognition: Application)
- **Li Wei** : Head up, listening, no verbal response (Emotion: Positive; Cognition: Understanding)
- **Liu Li** : Hand raised – “Uh... I think Zhu Ziqing... really liked spring... his words, um... show he really loved it.” (Emotion: Positive; Cognition: Understanding)
- **Zhang Tao** → **Liu Li** : Side talk – “**Liu Li**, can you explain how Zhu Ziqing shows his love for spring through language and imagery?” (Emotion: Confused; Cognition: Understanding)

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Teacher Feedback: “**Liu Li**, great participation and deep thinking—just be mindful of classroom order. **Zhang Yan**, well done with your insightful understanding of ‘Spring’—keep up the collaborative spirit.”

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3326**Case: Multi-Agent Interaction in "Spring" (Step 10)**3327
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Teacher Content: “Now let’s examine the structure of ‘Spring’. Zhu Ziqing divides the essay into three parts. First, he begins with anticipation: ‘Looking forward, looking forward, the east wind is coming, and spring’s footsteps are near.’ Then he uses vivid metaphors and delicate imagery to depict spring scenes like blooming trees. Finally, he uses personification—spring is a newborn baby, a little girl, a strong youth—bringing vitality to the season. This layered structure gives the essay rhythm and emotional resonance. **Zhang Jie**, would you like to share your understanding of this structure?”

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Teacher Emotion: Encouragement **Teacher Behavior:** Explanation
Student Responses:

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- **Wang Fang** → **Zhang Yan** : Side talk – “**Zhang Yan** ... you’re right... Zhu’s personification really shows the vitality and hope of spring!” (Emotion: Positive; Cognition: Application)
- **Zhang Jie** : Stand-up response – “Of course, teacher. I think the structure is brilliant. The beginning sets the tone of anticipation, the middle provides vivid descriptions, and the end gives spring symbolic meaning—energy, rebirth, youth. It’s rhythmic and emotionally deep.” (Emotion: Positive; Cognition: Application)
- **Zhang Yan** → **Wang Fang** : Side talk – “I’m glad you felt the vitality too, **Wang Fang**. His words awaken everything—dispelling winter and bringing hope.” (Emotion: Positive; Cognition: Application)

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- **Li Wei** → **Zhang Yan** : Side talk – “**Zhang Yan** , what’s your unique take on Zhu’s metaphors? I love his personification—it inspires our own writing, don’t you think?” (Emotion: Positive; Cognition: Understanding)
- **Liu Li** → **Zhang Tao** : Side talk – “**Zhang Tao** , I think Zhu’s vivid words reflect not just spring, but also his love for life and respect for nature.” (Emotion: Positive; Cognition: Understanding)
- **Zhang Tao** → **Liu Li** : Side talk – “Hmm, I like ‘Back Shadow’ more than ‘Spring’ . Have you read that one?” (Emotion: Positive; Cognition: Understanding)

Teacher Feedback: “**Zhang Jie** , wonderful—your structural analysis is spot on. **Liu Li** , your input shows a deep grasp of the text—keep it up! **Zhang Yan** , excellent discussion—maintain your positive attitude and spirit of exploration.”

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Case: Multi-Agent Interaction in "Dedication and Joy" (Step 12)

Teacher Content: “Now, let us explore the meaning of ‘finding joy in one’s work’ (*leye*). It refers to discovering happiness in our work or studies, enjoying what we do. In this way, our tasks become less of a burden and more of a pleasure. How does Liang Qichao interpret *leye*? In his essay, he writes, ‘Be at peace with your dwelling, and find joy in your work’—suggesting that we should experience peace and pleasure in what we do. **Zhang Jie** , could you share your understanding of *leye*? ”

Teacher Emotion: Encouragement **Teacher Behavior:** Questioning
Student Responses:

- **Wang Fang** : Note-taking – No verbal response (Emotion: Positive; Cognition: Understanding)
- **Zhang Jie** : Stand-up response – “I’m happy to share my view. I think *leye* means finding joy and value in what we do. As Liang Qichao said, ‘Be at peace with your dwelling, and find joy in your work’—to me, this means experiencing happiness and satisfaction through learning or working. When we love what we do, it becomes our source of joy rather than pressure.” (Emotion: Positive; Cognition: Application)
- **Zhang Yan** : Hand raised – “I think *leye* is about finding enjoyment in our learning or work. As Liang Qichao says, we should find peace and joy in our duties. That way, work becomes something we enjoy. This reflects my experience—I enjoy the learning process and hope others can find that joy too.” (Emotion: Positive; Cognition: Application)
- **Li Wei** : Hand raised – “I believe *leye* is about finding joy and satisfaction in the process of doing things. Liang Qichao’s quote applies not only to work but also to learning. If we find joy in learning, we’ll better understand knowledge and be more motivated. But I wonder, when facing stress or difficulties, how can we still embrace *leye*? ” (Emotion: Positive; Cognition: Application)
- **Liu Li** : Head down sleeping – No response (Emotion: Negative; Cognition: Memory)
- **Zhang Tao** → **Liu Li** : Chatting – “**Liu Li** , did you watch that basketball game yesterday? That dunk was insane!” (Emotion: Negative; Cognition: Memory)

Teacher Feedback: “**Liu Li** , great to see your improvement—keep participating actively. **Zhang Jie** , your engagement is excellent. **Zhang Yan** , you’ve shown strong understanding and communication—keep it up, and remember to listen to your peers.”

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Case: Multi-Agent Interaction in "Dedication and Joy" (Step 13)

Teacher Content: “Let’s now see how Liang Qichao argues for the importance of *leye*. In his essay ‘Dedication and Joy’ , he uses the phrase ‘Be at peace with your dwelling, and find joy in your work’ to explain his perspective. He believes that only when we feel peace and happiness in our duties can we truly understand what *leye* means. The ‘joy’ here refers not

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only to enjoyment but also to love and appreciation. **Zhang Jie** raised a great question: is *leye* limited to our work, or can it also apply to learning, life, and hobbies? **Li Wei**, what do you think?"

Teacher Emotion: Encouragement **Teacher Behavior:** Questioning
Student Responses:

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- **Wang Fang** : Note-taking – No response (Emotion: Positive; Cognition: Application)
- **Zhang Jie** : Question – “I fully agree with Liang Qichao. He helps us realize that only by loving our work can we find true joy and meaning in it. Then it’s not a burden anymore. But I have a question: can *leye* apply to things beyond work, like learning, life, or hobbies? I think anything we love deeply could be part of *leye*. What do you think, teacher?” (Emotion: Positive; Cognition: Application)
- **Zhang Yan** : Question – “Teacher, I’ve also been thinking about Liang’s view. He’s suggesting that when we genuinely love and enjoy what we do, it becomes a joy. This attitude should apply to learning as well—finding enjoyment rather than just completing tasks. But what if we’re not feeling that joy? How should we adjust our mindset?” (Emotion: Positive; Cognition: Application)
- **Li Wei** : Stand-up response – “Liang’s reasoning is inspiring. He shows that when we love what we do, it stops being pressure—it becomes joy. But I’m a bit confused about ‘being at peace with your dwelling.’ Does that mean we must accept and embrace our current life situation to experience *leye*? I’d love to hear others’ thoughts.” (Emotion: Positive; Cognition: Application)
- **Liu Li** : Head up listening – No response (Emotion: Positive; Cognition: Understanding)
- **Zhang Tao** : Head up listening – No response (Emotion: Positive; Cognition: Understanding)

Teacher Feedback: “**Zhang Yan**, your thoughtful and active participation is wonderful—keep it up! **Zhang Jie**, your engagement and depth of understanding help lead the class. **Li Wei**, your ideas are insightful—continue contributing in discussions!”

Case: Multi-Agent Interaction in "Dedication and Joy" (Step 14)

Teacher Content: “Your reflections have been fantastic. **Zhang Jie** asked a great question—can *leye* apply beyond work, such as to learning or hobbies? I believe *leye* is broad—it applies to any domain where we invest passion. As for **Zhang Yan**’s question about learning struggles: First, we must accept that difficulties are part of the process. Then, try to see them as challenges and growth opportunities. That’s how we rediscover joy in learning. Does anyone want to share how they’ve done this?”

Teacher Emotion: Encouragement **Teacher Behavior:** Questioning
Student Responses:

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- **Wang Fang** : Hand raised – “Uh, I... I think when we face learning difficulties... we shouldn’t give up. We... should accept them and... find solutions. If we stay optimistic, we’ll rediscover *leye*.” (Emotion: Positive; Cognition: Application)
- **Zhang Jie** : Stand-up response – “Teacher, I think *leye* is a broad concept—it definitely applies to learning, life, and hobbies. If we commit and love what we do, that’s *leye*. When facing challenges, we should adjust our mindset and find opportunities—that’s how we enjoy learning.” (Emotion: Positive; Cognition: Application)
- **Zhang Yan** : Stand-up response – “I agree. *Leye* means loving not just work but all aspects of life. When we face challenges in learning, changing our perspective helps us turn obstacles into joy. Has anyone had a similar experience? How did you regain your joy in learning?” (Emotion: Positive; Cognition: Application)
- **Li Wei** : Question – “Everyone’s ideas are inspiring. I also believe *leye* is a holistic attitude that includes work, learning, and hobbies. As long as we’re passionate,

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we'll find joy and self-worth. Though there may be difficulties, they are growth opportunities. I'd like to hear how others adjusted their mindset during such times." (Emotion: Positive; Cognition: Understanding)

- **Liu Li** : Head up listening – No response (Emotion: Positive; Cognition: Understanding)
- **Zhang Tao** : Head up listening – No response (Emotion: Positive; Cognition: Understanding)

Teacher Feedback: "Wang Fang , great focus and thinking—keep it up, and don't let anxiety affect your learning. Zhang Yan , your helpfulness and ability to apply learning are admirable—keep going!"

Case: Multi-Agent Interaction in "The Emperor's New Clothes"(Step 12)

Teacher Content: "Today, we will be reading *The Emperor's New Clothes*, a satirical tale by the famous Danish author Hans Christian Andersen. Andersen is one of the most renowned figures in children's literature, with a diverse range of works spanning fairy tales, novels, poems, and plays. Some of his most beloved stories include *The Little Match Girl*, *The Ugly Duckling*, and *The Little Mermaid*. In his fairy tales, Andersen often reveals human flaws and social injustice from a unique perspective, offering us valuable life lessons."

Teacher Emotion: Neutral **Teacher Behavior:** Lecture

Student Responses:

- **Wang Fang** : Head up listening – No response (Emotion: Positive; Cognition: Understanding)
- **Zhang Jie** : Question – "Teacher, I find this story very interesting. The emperor is tricked by two swindlers who claim that only intelligent people can see their fabric. The emperor never checks the clothes himself but sends others. I wonder—if he had gone himself, would he have seen through the deception? Or if he had the courage to admit he saw nothing, could he have avoided the embarrassment? This story not only mocks vanity and fear of losing face, but also reminds us to have the courage to face the truth. What do others think?" (Emotion: Positive; Cognition: Analysis)
- **Zhang Yan** : Question – "Teacher, this story made me reflect a lot. Andersen's works always carry deep meaning. Through this tale, he highlights human vanity and blind conformity, showing us the importance of honesty and truth. That's probably why his works remain so popular—they are both entertaining and meaningful. I also want to ask: does this story still hold relevance today? Don't we sometimes act like the emperor, pursuing superficial appearances while ignoring real value?" (Emotion: Positive; Cognition: Analysis)
- **Li Wei** : Question – "Teacher, I've also thought about what Zhang Jie and Zhang Yan said. To me, this story not only satirizes people who care too much about appearances, but also encourages independent thinking. That's a key takeaway Andersen wants us to have. I'd love to hear how others interpret it." (Emotion: Positive; Cognition: Analysis)
- **Liu Li** → **Zhang Tao** : Chatting – "Zhang Tao , have you watched the latest Marvel movie *Eternals*? I heard the plot is great and the effects are amazing. What did you think?" (Emotion: Negative; Cognition: Memory)
- **Zhang Tao** → **Li Wei** : Chatting – "Li Wei , do you think our school's football team will win this weekend's match?" (Emotion: Negative; Cognition: Memory)

Teacher Feedback: "Zhang Tao , please stay focused and participate actively so you can better understand the story. Liu Li , you show strong independent learning ability, but classroom interaction is important too—try joining the discussion!"

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Case: Multi-Agent Interaction in "The Emperor's New Clothes"(Step 13)

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Teacher Content: “Students, the questions raised by **Zhang Jie** , **Zhang Yan** , and **Li Wei** were excellent and show deep thinking about the story. Now, can anyone tell me what genre *The Emperor's New Clothes* belongs to? Is it a novel, a poem, an essay, or a fairy tale?”

Teacher Emotion: Encouragement **Teacher Behavior:** Questioning

Student Responses:

- **Wang Fang** : Note-taking – No response (Emotion: Positive; Cognition: Application)
- **Zhang Jie** : Stand-up response – “I think it's a fairy tale. The plot—like the emperor being deceived—is common in fairy tales. And it teaches us a lesson: to think independently and not blindly follow others.” (Emotion: Positive; Cognition: Analysis)
- **Zhang Yan** : Stand-up response – “I agree—it's a fairy tale. Although the characters are familiar—like emperors and tailors—the story includes magical elements such as invisible clothes and collective pretending. It also teaches a moral, which is typical of fairy tales.” (Emotion: Positive; Cognition: Application)
- **Li Wei** : Stand-up response – “I also think it's a fairy tale. It includes fantasy elements and makes us think deeply. But I'd also like to hear what others think.” (Emotion: Positive; Cognition: Application)
- **Liu Li** : Head down reading – No response (Emotion: Negative; Cognition: Understanding)
- **Zhang Tao** → **Liu Li** : Chatting – “**Liu Li** , what book are you reading? It looks interesting.” (Emotion: Negative; Cognition: Understanding)

Teacher Feedback: “**Liu Li** , let's try to stay focused—your intelligence should be used to understand the story. **Wang Fang** , your thoughtful interpretation is excellent—please keep sharing. **Zhang Tao** , let's all focus on the lesson—we're eager to hear your ideas too.”

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Case: Multi-Agent Interaction in "The Emperor's New Clothes"(Step 14)

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Teacher Content: “Great work, everyone. **Zhang Jie** mentioned that if the emperor had the courage to admit he couldn't see the fabric, he could have avoided embarrassment—a sharp observation. **Zhang Yan** asked about the story's modern relevance, and that's a very valuable question: do we, too, sometimes pursue surface appearances and ignore real value? **Li Wei** talked about the importance of independent thinking—something we should all cultivate. We'll continue exploring these ideas in future lessons.”

Teacher Emotion: Encouragement **Teacher Behavior:** Questioning

Student Responses:

- **Wang Fang** : Head up listening – No response (Emotion: Positive; Cognition: Analysis)
- **Zhang Jie** : Stand-up response – “I think this story is really meaningful. Like **Zhang Jie** said, the emperor's fear of embarrassment kept him from facing the truth. This happens in real life too. The story teaches us to be brave and value independent thinking—just like **Li Wei** said. I'll try to apply this understanding in the future and learn from my classmates' views as well.” (Emotion: Positive; Cognition: Analysis)
- **Zhang Yan** : Stand-up response – “I agree with both **Zhang Jie** and **Li Wei** . Courage and critical thinking are crucial. I'd add that in chasing a beautiful life, we shouldn't lose sight of what's real. Like the emperor, we risk embarrassment when we chase appearances. This story warns us not to be modern-day emperors.” (Emotion: Positive; Cognition: Analysis)
- **Li Wei** : Stand-up response – “Thank you, teacher. I agree with **Zhang Jie** 's point about courage and **Zhang Yan** 's insights on modern relevance. We often do focus too much on appearance and forget real values. This story encourages us to think

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independently, face truth, and care about substance over form.” (Emotion: Positive; Cognition: Analysis)

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- **Liu Li** → **Zhang Yan** : Chatting – “**Zhang Yan** , have you seen that popular TV show *Green Fields Under Moonlight*? The characters are so well-written. You should check it out.” (Emotion: Negative; Cognition: Understanding)
- **Zhang Tao** → **Li Wei** : Chatting – “**Li Wei** , did you notice **Liu Li** was chatting during class? Do you know what they were talking about?” (Emotion: Negative; Cognition: Understanding)

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Teacher Feedback: “**Wang Fang** , great job observing and thinking—don’t be anxious, we’re all learning together. Try sharing your ideas next time. **Zhang Yan** , your active participation and deep thinking are a real asset to the class. **Zhang Jie** , your analytical skills and eloquence are excellent—keep up the enthusiasm!”

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