**Agent4Edu:** **Generating** **Learner** **Response** **Data** **by** **Generative** **Agents**

**for** **Intelligent** **Education** **Systems**

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**Abstract**

Personalized learning represents a promising educational strategy within intelligent educational systems, aiming to en- hance learners’ practice efficiency. However, the discrepancy between offline metrics and online performance significantly impedes their progress. To address this challenge, we in- troduce **Agent4Edu**, a novel personalized learning simula- tor leveraging recent advancements in human intelligence through large language models (LLMs). Agent4Edu features LLM-powered generative agents equipped with learner pro- file, memory, and action modules tailored to personalized learning algorithms. The learner profiles are initialized us- ing real-world response data, capturing practice styles and cognitive factors. Inspired by human psychology theory, the memory module records practice facts and high-level sum- maries, integrating reflection mechanisms. The action module supports various behaviors, including exercise understand- ing, analysis, and response generation. Each agent can in- teract with personalized learning algorithms, such as com- puterized adaptive testing, enabling a multifaceted evaluation and enhancement of customized services. Through a com- prehensive assessment, we explore the strengths and weak- nesses of Agent4Edu, emphasizing the consistency and dis- crepancies in responses between agents and human learn- ers. The code, data, and appendix are publicly available at <https://github.com/bigdata-ustc/Agent4Edu>.

**1** **Introduction**

Intelligent education platforms like *Coursera.com* and *Leet-* *Code.com* provide a rich array of learning resources, such as courses and exercises, within a flexible online environ- ment. The accessibility and convenience of these platforms have attracted a growing number of learners. A key online learning activity is “practice”, where learners independently select and answer exercises. The platforms record their re- sponses, such as the correctness of their answers. By ana- lyzing response data, many personalized learning services, such as exercise recommendations, knowledge tracing, and computerized adaptive testing, can be tailored to meet each learner’s specific needs, enhancing the learning process and increasing learner satisfaction. For instance, on *LeetCode*,

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analyzing a learner’s historical programming experiences al- lows the platform to recommend exercises of appropriate difficulty levels, thus optimizing learning gains.

The effectiveness of personalized learning services hinges on the availability of high-quality response data for the cor- responding algorithm training. However, the scarcity of of- fline response data and potential biases in its correlation with online practice introduces a significant gap between offline metrics and actual online performance. This discrepancy im- pedes the integration of research with real-world applica- tions. To bridge this gap, a promising approach is to simulate learner response data. Imagine an online platform equipped with a configurable simulation system that faithfully cap- tures human learners’ response patterns while seamlessly in- teracting with personalized learning algorithms. Such a sim- ulator undoubtedly has the potential to revolutionize the tra- ditional research paradigm in intelligent education, provid- ing innovative avenues for response data collection, person- alized algorithm development and evaluation.

Several approaches to simulating learner response data have been proposed and have achieved notable suc- cess (Piech et al. 2015; Zhao et al. 2023). However, two major limitations exist in current approaches: (1) **Simpli-** **fied** **Simulations.** Most existing studies predict learners’ re- sponses (e.g., correct or incorrect answers) without consid- ering the detailed answer processes by which humans use their knowledge to understand, analyze, and solve prob- lems. Hence, these simulations may lack reliability and in- terpretability. (2) **Dependency** **on** **Real** **Response** **Data.** An ideal simulator should be capable of simulating learner responses even when real-world datasets are insufficiently available, thereby enhancing its applicability. However, cur- rent methods require high-quality real-world data to train the simulation strategy. As a result, these methods can only generate learner response data similar to existing real-world datasets and struggle to generalize to more challenging sce- narios, such as zero-shot simulations.

Recent advancements in large language models (LLMs) have demonstrated remarkable capabilities in autonomous interaction and decision-making (Brown et al. 2020; Ouyang et al. 2022; Yue et al. 2023; Jin et al. 2023; Long et al. 2024). These advancements underscore the potential of leverag- ing LLM-powered agents to simulate human social behav-

iors, such as daily life in Smallville (Park et al. 2023) and software development (Qian et al. 2023). LLM-based user simulators possess rich pre-trained knowledge and human- like intelligence, enabling them to perceive and simulate intricate human practice processes. Furthermore, their in- context learning ability allows LLMs to perform zero-shot simulations with minimal reliance on real-world data (Wang et al. 2023c). Consequently, LLM-based generative agents present a promising approach for addressing the current lim- itations of learner response simulators.

In this paper, we introduce **Agent4Edu**, a personalized learning simulator designed for intelligent educational sys- tems, comprising two key components: an **LLM-powered** **generative** **agent** and a **personalized** **learning** **environ-** **ment** (see the framework in Figure 1). From a learner per- spective, the LLM-powered generative agent is responsible for simulating learners’ response data by capturing their re- sponse patterns and inferring problem-solving actions. Each agent is initialized based on available learner response data and consists of three modules: a learner profile, memory, and action module. The learner profile module stores learners’ past practice styles (e.g., *activity*) and cognitive factors (e.g., *ability*), aligning with human learners’ learning status. The memory module, inspired by psychological theories (Baker 2001) and human learning mechanism (Wang et al. 2023d), records past practice experiences and summarizes learn- ing status through reflections. This facilitates coherent ob- servations, monitors *knowledge* *proficiency* *evolution*, rein- forces memory, and simulates human forgetting. The action module enables agents to choose, understand, analyze, and solve exercises recommended by personalized learning algo- rithms, leading to more reliable and interpretable response generation. Our agent can also utilize tools, such as em- ploying the psychological IRT model (Baker 2001) to as- sess *ability* within the Profile module and using DNeural- CDM (Wang et al. 2023a) to trace *knowledge* *proficiency* *evolution* within the Memory module. From a personalized learning perspective, the learning environment can be con- figured with any personalized learning algorithm, allowing agents to interact directly and simulate a real learning en- vironment. Notably, despite extensive research on simulat- ing user behavior with generative agents, we are the first to focus specifically on educational scenarios to generate re- sponse data for individual learners.

Our main contributions are summarized as follows:

• We develop Agent4Edu, a personalized learning simulator that leverages LLM-powered generative agents to simu- late human learners’ response data as well as demonstrate the practice process. Additionally, the agent interacts with personalized learning environments to evaluate and im- prove intelligent tutoring algorithms.

• Our generative agents, featuring profile, memory, and action modules specifically designed for “Education”, can not only generate response data but also accurately simulate human choices, understanding, analysis, and problem-solving for exercises, outperforming existing learner simulation methods.

• To systematically evaluate Agent4Edu, we conduct com-

prehensive experiments from both the agent and person- alized learning perspectives. From the agent perspective, we assess the consistency between the agents and human learners. From the learning perspective, we evaluate and improve personalized learning algorithms for computer- ized adaptive testing, based on generative agents and sim- ulated data. Extensive experimental results demonstrate the effectiveness of Agent4Edu.

**2** **Related** **Work**

**Learner** **Response** **Data** **Simulation** Learner Simulation aims to address the shortage of high-quality practice data in intelligent educational systems and has been applied in numerous previous studies (Zhao et al. 2023; Yao et al. 2024). Memory-based (Reddy, Levine, and Dragan 2017) re- lies on manually crafted rules to predict learners’ responses or memory behavior. EERNN (Su et al. 2018) and KES (Liu et al. 2019) utilize RNN-based models to forecast learn- ers’ performance. DAISim (Zhao et al. 2023) constructs learner simulations as Markov decision processes, simulta- neously considering learners’ long and short-term question- answering patterns. However, the memory-based simulator is overly simplistic and cannot simulate complex interac- tions. Most other learner simulators simplify the student an- swering process and face challenges in conducting zero-shot simulations due to their reliance on data. In this paper, we employ an LLM-powered agent to simulate the student prac- tice process, addressing these limitations.

**Personalized** **Learning** **Services** Intelligent educational systems offer learners personalized learning services, in- cluding Computerized Adaptive Testing (CAT) (Chang and Ying 1996), exercise recommendation (Huang et al. 2019) and learning path suggestions (Liu et al. 2019), to help learn- ers enhance their skills. In this work, we select the represen- tative and popular CAT services as our personalized learning scenarios for our study and experiments. CAT is an advanced educational measurement method that evaluates the knowl- edge level of examinees in minor exercises, which has been widely used in various standardized tests (e.g., GMAT and GRE) (Zhuang et al. 2024; Bi et al. 2020; Lord 2012; Chang and Ying 1996). However, current CAT models require high- quality practice data to train a cognitive diagnosis model for evaluating learner ability or knowledge proficiency, which is often challenging to gather. Therefore, in this paper, we employ the CAT service within learning systems to assess the quality of the data generated by our agents. Addition- ally, we investigate the potential for enhancing CAT models using simulated data.

**LLM-based** **Agents** LLM-based generative agents demon- strate the remarkable capabilities to perceive their environ- ment, make decisions, and take actions, thus, emerging a substantial amount of research (Wang et al. 2024b). The development of generative agents (Park et al. 2023), de- signed with profile, memory, action, and reflective capa- bilities, represents pioneering work in simulating human daily life. Within this general framework, agents tailored to specific tasks (Qian et al. 2023; Wu et al. 2023; Wang et al. 2023b; Huang et al. 2023; Zhang et al. 2023b,a) and simulations (Gao et al. 2023; Wang et al. 2023d; Park

et al. 2023; Liu et al. 2023; Wang et al. 2023c) have been constructed. Recent research highlights bringing generative agents to educational settings (Li et al. 2024; Dan et al. 2023; Kieser et al. 2023). For example, (Qadir 2023; Rahman and Watanobe 2023) conclude the applications of ChatGPT to engineering education. (Baidoo-Anu and Ansah 2023) focus on the literature review over the published paper. Socrati- cLM (Liu et al.) embodies a “Thought-Provoking” teaching paradigm, engaging students in active problem-solving, akin to a real classroom teacher. The most relevant part of our work is EduAgent (Xu, Zhang, and Qin 2024) which uti- lizes LLM-based agents to simulate learners studying Pow- erPoint presentations and videos, predicting their quiz out- comes to assess performance. However, this approach re- lies on expert-annotated cognitive factors to initialize agents, disregarding the understanding and analysis of exercises. In contrast, our Agent4Edu extracts cognitive factors from data using tools and captures practice styles, allowing it to sim- ulate the detailed exercise understanding and analysis pro- cess and interact effectively with personalized learning al- gorithms.

**3** **Agent4Edu**

Agent4Edu is a personalized learning simulator, aimed at accurately simulating learners’ response data and facilitat- ing responsive personalized learning algorithms. It contains two key components: (1) LLM-powered generative agents that capture learners’ practice patterns and cognitive pref- erences to simulate their response, and (2) a personalized learning environment that interacts with agents to support accurate and interpretable evaluations and improvements of mainstream intelligent algorithms (e.g., computerized adap- tive testing). The framework of Agent4Edu is illustrated in Figure 1. All the prompts are listed in Appendix C.

**3.1** **Task** **Formulation**

Suppose there are |U| learners, |E| exercises in an in- telligent educational system. For a learner u ∈ U, his/her response data are denoted as a time-ordered set lu = {(e1 , ce1 , yu,e1 ), (e2 , ce2 , yu,e2 ), . . . , (en , cen , yu,en )}, where ei ∈ E represents the exercise that learner u practiced at step i, and yu,ei is u’s response to exercise ei , which is usually denoted as a binary value, i.e., if learner u answers ei correctly, yi = 1 otherwise yi = 0. ce denotes textual information of each exercise e ∈ E, e.g., textual content and corresponding knowledge concepts. We provide ce in a < key, value > form, as the example in Figure 1.

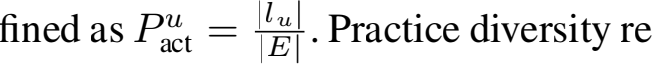
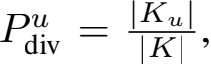
Based on the above conditions, the simulator’s overarch- ing goal is to faithfully distill the human learners’ learning patterns and cognitive preferences, and accurately generate their future response data on unseen exercises. Please note that existing personalized learning algorithms usually as- sume that learners only submit each exercise once, so re- peated submission is not considered in our simulation.

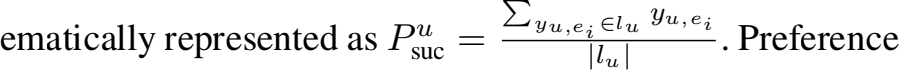
**3.2** **LLM-powered** **Agent**

The generative agent in Agent4Edu uses LLM as its foun- dational architecture, enhancing its functionality tailored for

the personalized learning scenario through three specialized modules: learner profile, memory, and action modules. To mimic actual personalized practice responses akin to hu- mans, we construct an individual agent agentu for each learner u. Each agent integrates a learner profile module aimed at reflecting personalized practice patterns and cog- nitive factors. Additionally, each agent is equipped with a memory module designed to store past practice records and summarize high-level ideas. To simulate learner practice be- havior more cohesively, the agent is also equipped with an action module.

**Learner** **Profile** **Module** The learner profile module rep- resents some overall learning features of human learners, which are typically stable and derived from long-term learn- ing experiences. We configure each agent agentu’s profile based on its corresponding learner u’s response data1. Each agent’s initial configuration is divided into two categories: explicit practice styles and implicit cognitive factors.

Practice styles are statistical features explicitly derived from the available practice record lu of each learner u, such as learning activity (Baker 2001; Gao et al. 2021), practice diversity (Bi et al. 2020), success rate, and preference. Activ- ity indicates learners’ enthusiasm for learning and provides clues for simulating their practice behaviors. For example, learners with higher enthusiasm for learning usually perform better. Mathematically, the activity level of learner u is de- flects the knowledge coverage practiced by learners, represented as  where |Ku | is the number of knowledge concepts practiced by learner u. Higher diversity indicates greater curiosity in learners. Success rate correlates with the probability of learners answering questions correctly, making it another es- sential characteristic. The success rate for learner u is math-



refers to the knowledge concepts that learners practice most frequently.

Cognitive factors are implicit features studied in psychol- ogy (Baker 2001; Chen et al. 2024), which significantly im- pact learner u’s practice performance. We select problem- solving ability and knowledge proficiency (Cheng et al. 2024) for this study. Problem-solving ability is assumed to be stable during the learning process, while knowledge proficiency typically evolves with learning progress (Huang et al. 2020). Therefore, in the profile module, we only con-

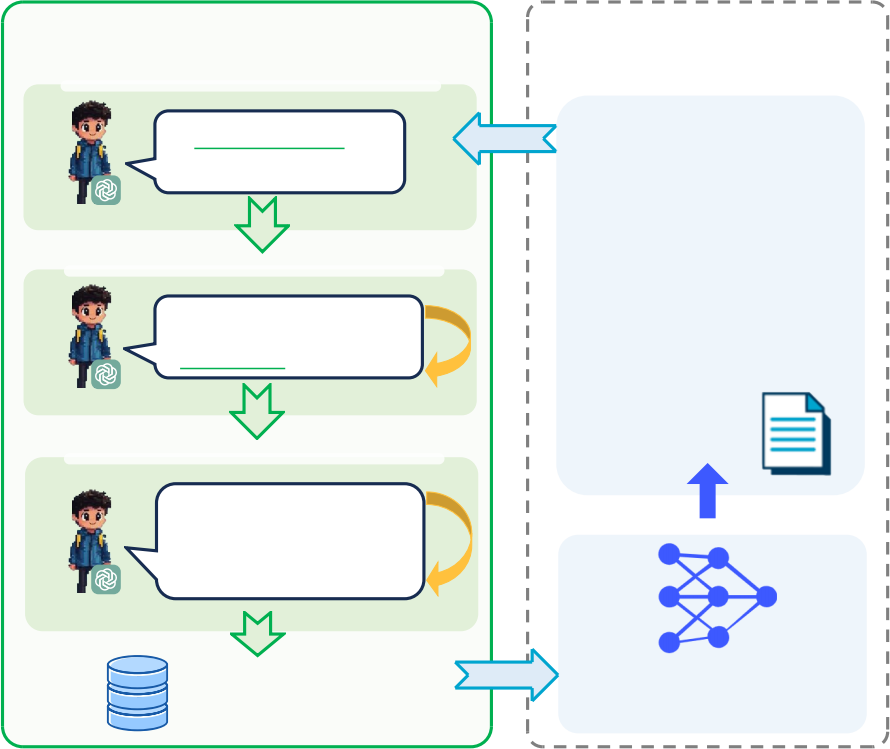
figure the ability factor P, with knowledge mastery being

considered in the subsequent memory module. To obtain im- plicit ability, we assign a psychological IRT model (Baker 2001) trained on the observed learner response records, as the tool for the agent, allowing it to infer each learner u’s ability factor from the response data lu. The training and use of the IRT tool are detailed in Appendix B.

Notably, we segment the values of each of the above fea- tures into several tiers in order to better prompt the gen- erative agent inspired by (Wang et al. 2023d). For a de-

1Note that if zero-shot simulations are performed and user data is unavailable, the profile needs to be randomly generated.

**Real** **Response** **Data**

**Action** **Module**

**Memory** **Module** **Factual** **Memory**

**…** fu, 1 fu,2 fu,3 fu,4 fu,5

**Personalized** **Learning**

**Exercise**

**[Key]:** **Textual** **Content** **[Value]:** **Will** **the** **graph** **of** **the** **function** **y=a^x-3** **always** **pass** **through**

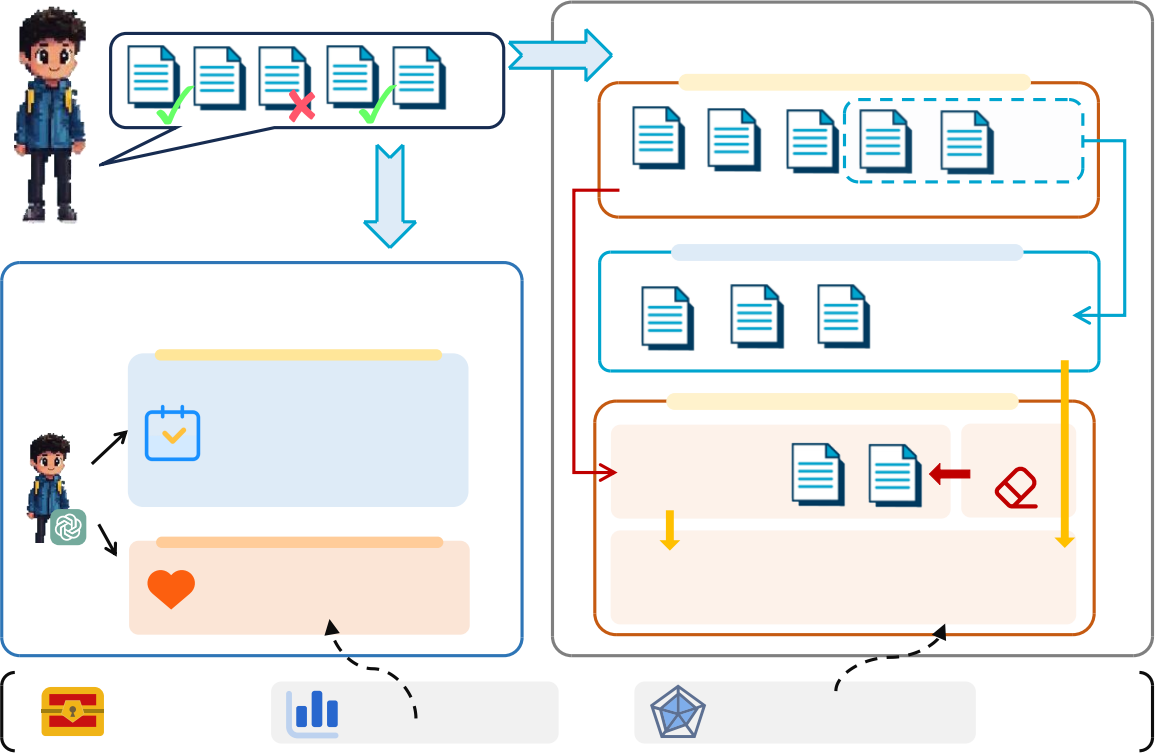
**the** **point** **(1,** **a)?**

**Cognitive-driven** **Action**

**…**

**I** **choose** **to** **do** **this** **exercise** **…**

**Learner** u

**Short-term** **Memory**

**Reading** **&** **Understanding** **It** **tests** **knowledge**

**Learner** **Profile** **Module**

**Practice** **Features**

**Activity:** **High**

**Most** **Recent** **Observations**

***Function*** **…**

**(Reflection)**

**Long-term** **Memory**

**.** **.** **.**

**Diversity:** **High**

**Analyzing** **&** **Solving**

**Forget**

**Reinforced** **Facts**

**Summary**

**(Reflection)**

**Success** **Rate:** **Easy**

**.** **.** **.**

**Since** **the** **function** **is** **y=a^x-3,** **we** **can** **substitute** **the** **…**

**Cognitive** **Factors** **Ability:** **Middle**

**Learning** **process:** **…**

**Proficiency:** **…**

**(Reflection)**

**Simulated**

**Personalized** **Learning**

**Algorithm**

**Response** **Data**

**Tools:**

**.** **.** **.**

**DNeuralCDM**

**IRT** **Model**

**LLM-empowered** **Agent** agentu **Environment**

Figure 1: The overall framework of Agent4Edu.

tailed exposition, refer to Appendix A.1. Additionally, to en- sure broad applicability and protect privacy, certain personal identifiers (such as name, gender, age, and occupation) are intentionally anonymized in this work (Zhang et al. 2023a; Li et al. 2023). While these attributes may help shape other types of agents, they are not primary factors affecting prac- tice performance in education. Our approach, based on both behavioral practice styles and psychological cognitive set- tings, can support a comprehensive representation of real learners.

**Memory** **Module** The Memory module allows the LLM- based agent agentu to observe and summarize its corre- sponding learner u’s past practice experiences step by step. This module provides insightful clues to the agent for re- sponse simulation on unseen exercises. We follow the hu- man learning mechanism (Atkinson 1968a; Cowan 2008; Huang et al. 2020; Wang et al. 2023d) to design three types of memories for each agent: *factual* *memory*, *short-term* *memory*, and *long-term* *memory*. Each memory is initially set to empty.

• *Factual* *Memory*: In our simulation, factual memory is de- fined as the true learner’s past response records (i.e., *obser-* *vations*). When the agent obtains a new response record of learner u at step i, i.e., lu,i = (ei , cei , yu,ei ), the response record is transmitted to the factual memory for processing. Inspired by human learning mechanisms, if an agent re- peatedly practices similar questions or knowledge, their memory is strengthened (Huang et al. 2020). Therefore, we introduce an additional counter fu,i (initially set to 1) for each record lu,i in factual memory to track the num- ber of times it has been reinforced, a simple yet effec- tive method that has been successfully used in user pref- erence simulation (Wang et al. 2023d). Formally, for each agent agentu , assume it has observed n factual memories is Mu = {lu,1, lu,2,..., lu,n }, then it is allowed to receive a new response record lu,n+1. We first calculate the similarity

between lu,n+1 and each existing factual memory lu,i in the current memory Mu. The similarity between records can be defined as a metric that can be evaluated by LLMs, cosine similarity between text vectors, and other similar measures. In this case, we use the similarity relationships between the knowledge concepts involved in the records for the calcu- lation. Specifically, we employ the statistical tool2 released by RCD (Gao et al. 2021) to determine whether two knowl- edge concepts are similar. If there is a similarity between the knowledge concepts involved in two records, the two records are considered similar. For similar records, we increment the counter for lu,i by 1 (i.e., fu,i ← fu,i + 1), indicating that it has been reinforced by lu,n+1, and then add lu,n+1 to fac- tual memory; otherwise, lu,n+1 is directly recorded without any reinforcement. After processing and saving a new re- sponse record, factual memory triggers updating *short-term* and *long-term* *memories*.

We emphasize that the agent can only save response records into factual memory but cannot directly retrieve it, thereby allowing the retention of all exercise textual in- formation and responses without being constrained by the LLM’s context length limitations.

• *Short-term* *Memory*: Human short-term memory refers to the recent and temporary information that can be re- tained and recalled over a relatively brief period (Atkin- son 1968b). Therefore, in our simulation, short-term mem- ory is employed to retain the details of the agent’s most re- cent observed s records. Assuming the current factual mem- ory of agent agentu is Mu = {lu,1, lu,2,..., lu,n }, then the short-term memory storage is defined as Mu,short = {lu,n-s+1,..., lu,n }.

• *Long-term* *Memory*: Long-term memory is formed through the reinforcement of memories from repeated practice and self-reflection inspired by to human long-term memo- ries (Matelsky et al. 2023). It possesses a wide receptive

2<https://github.com/bigdata-ustc/RCD>

field, allowing it to retain information observed long ago and generate high-level insights. We design the long-term memory using three types of information: (1) **Reinforced** **Facts**: During each update of long-term memory, the agent agentu first goes through the current factual memory Mu. When the count fu,i of a record lu,i exceeds a preset thresh- old F, indicating that the memory has been reinforced F times, it is converted into long-term memory. (2) **Learn-** **ing** **Process** **Summary**: We utilize the LLM embedded in the agent to summarize the agent’s learning status from both short-term and long-term memories by *Memory* *Reflection*. Each step of the summary replaces the previous summary. The summary consists of linguistic descriptions of the prac- tice process and new insights from the agent itself. It over- looks practice details to filter out noise, irrelevant content, or potentially misleading information. Furthermore, compress- ing memory conserves significant space and enhances op- erational efficiency. (3) **Knowledge** **Proficiency**: We allow the agent to use an optimized DNeuralCDM (Wang et al. 2023a) based on the observed learner response data as a tool to obtain the learner’s dynamic proficiency (segmented into several tiers) evolution of specific knowledge concepts af- ter each step of practice. The knowledge proficiency is a kind of dynamic cognitive factor significantly reflecting hu- man responses in education (Piech et al. 2015; Wang et al. 2024a). The training and use of DNeuralCDM are given in Appendix B.

Additionally, each factual record in long-term memory may be **forgotten** following the human forgetting curve the- ory (Averell and Heathcote 2011; Huang et al. 2020) that hu- man memory decay starts rapidly and then gradually slows over time. We define a forgetting function associated times-



to simulate human learners’ forgetting. For each factual record in the long-term memory Mu , it is forgotten if g(lu,i ) exceeds a predetermined threshold λ and its reinforcement frequency fu,i in factual memory is then reset as 1.

Overall, the factual response records are specific, while learning memory summaries are more general. By combin- ing them, the agent can accurately perceive the learner’s practice process. Please note that traditional simula- tors (Piech et al. 2015; Zhao et al. 2023) can be regarded as owning the short-term memory but no long-term memory.

To help agents interact with the personalized learning en- vironment, we introduce three memory operations:

• *Memory* *Retrieval*: This operation assists the agent in ex- tracting related information from memory. We allow the agent to retrieve the short-term and long-term memories finding reinforced facts and conducting summary.

• *Memory* *Writing*: The raw observations are firstly input into the factual memory as facts. Then the recent facts are stored in short-term memory and the reinforced facts are written into long-term memory.

• *Memory* *Reflection*: This operation occurs exclusively within long-term memory containing two aspects of reflec- tions: (1) **Summary** **Reflection** is performed to summarize high-level ideas based on short-term and long-term mem- ories, and (2) **Corrective** **Reflection** is performed when the agent’s action is inconsistent with the real learner, which will

be introduced in Action Module.

**Action** **Module** To equip the agent with learner profiles and memory modules, enabling it to exhibit human-like problem-solving behaviors and responses based on current observations, we design a specialized action module for each agent within Agent4Edu tailored for personalized learning. This module encompasses three main categories of actions:

• *Cognitive-driven* *Actions*: In our simulation, personalized learning algorithms recommend one exercise to the agent at each step. The agent read the exercise’s content and decides whether or not to practice it, based on current cognitive fac- tors. If the exercise is too challenging relative to the agent’s assessed ability and knowledge proficiency, the agent can opt to reject the recommended exercise.

• *Reading* *and* *Understanding* *Exercises.* Simulating the process of reading and understanding exercises, similar to how humans approach them, provides valuable and inter- pretable insights into the agents. During each practice ses- sion, the agent is first required to identify and describe a knowledge concept assessed by the current exercise. If the agent correctly matches the exercise’s knowledge concept, it demonstrates an understanding of the exercise context akin to human learners. If the agent fails to do so, a corrective reflection is triggered to guide the agent towards the cor- rect knowledge concept. This method reduces the risk of in- accuracies and ensures the agent’s credibility in simulating learner response (Zhang et al. 2023a).

• *Analyzing* *and* *Solving* *Exercises.* Analyzing and solving exercises are crucial aspects of the learning process. Un- like previous simulation methods that directly predict the learner’s response in terms of answer correctness, our simu- lation requires the agent to emulate the learner’s answering process, which enhances both interpretability and credibil- ity. To simulate this complex answer process more effec- tively, we improve agent’s reasoning ability through a chain- of-thought approach (Wei et al. 2022). Initially, the agent combines its profile and memories to formulate an initial solution idea for the exercise. Then, it writes the final an- swer to the exercise based on the solution idea. Afterwards, the agent predicts whether its answer is correct (i.e., perfor- mance prediction). If the predicted response does not match the real learner’s response, a corrective reflection is trig- gered. Note that, if standard answers of exercises are avail- able, a scoring program can be designed to directly assess the correctness of the agent’s answer.

**3.3** **Personalized** **Learning** **Scenarios**

Agent4Edu simulates agent and learning environment inter- action (see Appendix D for a case study). The learning en- vironment is designed as a standalone module that incorpo- rates a series of personalized algorithms. These algorithms can recommend exercises to agents based on their past prac- tice data. For instance, our experiments utilize computerized adaptive testing (CAT) strategies (Bi et al. 2020) for per- sonalized learning. The module features an open interface, allowing researchers and practitioners to integrate external personalized learning algorithms seamlessly. This adaptabil- ity ensures that Agent4Edu serves as a versatile platform for

comprehensive evaluations and the future collection of valu- able learner response data.

**4** **Experiment**

**Dataset** Our dataset, called *EduData*, is provided by iFLY- TEK Co., Ltd. It comprises 18,045 time-ordered response records from 500 Chinese high school students in the sub- jects of mathematics and physics. Each record includes the exercise ID, correctness, and timestamp. There are 1,032 ex- ercises and 458 knowledge concepts in total, with each ex- ercise testing one knowledge concept. Additionally, to fa- cilitate reasoning and reflection for LLM-based agents, the platform provider has furnished us with the textual content of the exercises. In the experiment, we translate all Chinese text of exercises into English.

**Experimental** **Setup** We use GPT-3.5-turbo and GPT-4 through OpenAI’s API service 3 to construct the agent for experimentation. When operating under the GPT-3.5-turbo configuration, all response data is utilized for experiments. Due to cost considerations, we simulate the task records of only 100 learners under the GPT-4 setting. The temperature parameter of GPT is 0 to avoid randomness. Empirically, we set the short-term memory size to 5, the threshold F for memory enhancement is 5, and the threshold λ for forgetting in long-term memory is 0.99. Note that, in our experiments, unless explicitly specified, the LLM used is GPT-3.5-turbo.

**4.1** **LLM-based** **Agent** **Simulation** **Evaluation**

***Motivation*:** The LLM-based agent is the core component of Agent4Edu. Exploring whether the agent can truly simu- late human learners’ practice response is crucial for enhanc- ing intelligent educational systems. We evaluate the effec- tiveness of the generative agent, including response simula- tion, exercises’ knowledge understanding, zero-shot simula- tions, and ablation experiments.

**Learner** **Simulation** **Evaluation** The agent aims to gen- erate simulated learner response data that closely approx- imates real responses. To validate the effectiveness of the simulation, we compare it with two traditional supervised simulation methods, including DAISIM (Zhao et al. 2023) and KES (Liu et al. 2019). Additionally, to enrich our baseline for a compelling comparison, we include several Knowledge Tracing (KT) models, such as DKVMN (Zhang et al. 2017), EERNN (with Markov) (Su et al. 2018) and SAKT (Pandey and Karypis 2019), which are similar to the learner simulator in terms of response prediction.

In the experimental setup, each learner’s records are di- vided into a 90% training set and a 10% test set. Each base- line model which is data-driven is trained on the training data, with the last 20% records of each learner’s training data used for model validation. The agent has access to all train- ing data to generate profiles and update its memory through reflection. During the testing phase, each trained baseline is tasked with predicting learners’ binary responses (correct or

3The detailed GPT versions: GPT-3.5-turbo-1106 (up to Sep.

2021) and GPT-4-turbo (up to Dec. 2023).

Table 1: Prediction scores (%) on evaluating simulation per- formance. The best results are bold, the second-best results are marked by an underline, and ↑ means the higher score the better performance, the same as below. Agent4Edu100 indicates a basic exploratory on simulating 100 learners.

|  |  |  |  |
| --- | --- | --- | --- |
| Model | ACC ↑ F1-score ↑ ROUGE-3 ↑ | | |
| KES | 50.11 | 58.32 | 25.77 |
| DKVMN | 64.39 | 76.70 | 37.24 |
| EERNN | 65.72 | 76.06 | **43.55** |
| SAKT | 65.52 | 78.33 | 31.09 |
| DAISIM | 65.63 | 78.25 | 31.72 |
| Agent4Edu (GPT-3.5-turbo) | **66.70** | **79.84** | 37.97 |
| Agent4Edu (GPT-3.5-turbo)100 | 65.40 | 78.72 | 35.14 |
| Agent4Edu (GPT-4)100 | 66.51 | 79.53 | 34.86 |

incorrect) to unseen exercises in the test data. For our gen- erative agent, exercises from the test data are sequentially sent to it, and it performs the designed three actions to solve them. If the agent rejects an exercise due to its difficulty, we label its response as an “incorrect answer”. The eval- uation metrics are selected from two perspectives. Firstly, we use accuracy (ACC) and F1-score to measure predic- tion accuracy. Secondly, we assess the similarity between the simulated and real data distributions using ROUGE-3, inspired by (Zhao et al. 2023). We repeatedly run each base- line model five times in the same setups and the Table 1 reports the average scores.

The experimental results indicate that Agent4Edu (GPT- 3.5-turbo) demonstrates strong competitiveness compared to the supervised baselines, particularly in terms of ACC and F1-score. This suggests that the LLM-based agent has the potential to generate learner response data that closely re- sembles real-world datasets. Furthermore, among the base- lines, EERNN performs exceptionally well by effectively modeling the exercise content as supplementary clues. Fi- nally, an exploratory simulation conducted using Agent4Edu (GPT-3.5-turbo and GPT-4) on a subset of data with 100 learners shows that they enable the simulated distribution to closely approach the real distribution. Among them, GPT-4 performs better in terms of ACC and F1-score.

Additionally, we evaluate whether the simulated distribu- tion of the agent’s practice success rate aligns with the actual distribution of learner data. We use the real response success rate as the ground truth and then replace the corresponding responses in the real sequence with the predicted responses from the test data to calculate the agent’s simulated success rate, as shown in Figure 2 (a). The comparison between the ground truth values and the agent’s results indicates that the simulated data effectively captures the learners’ practice pat- terns related to success rate.

**Understanding** **Exercise-related** **Knowledge** To evalu- ate whether the agent understands a specific exercise, the agent is tasked with generating the knowledge concept tested by the exercise. Specifically, we create a candidate list con- taining one actual knowledge concept related to the exercise and two random knowledge concepts unrelated to the ex- ercise. The agent must then select the relevant knowledge

1.0

0.8

0.6

0.4

0.2

1.0

0.8

0.6

0.4

0.2

**(a)**

1.0

0.8

0.6

0.4

0.2

0.0

1.0

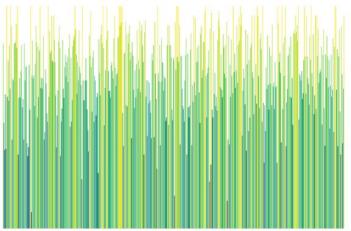
0.8

0.6

0.4

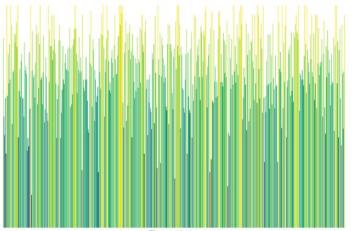
0.2

0.0



|  |
| --- |
| **Ground-truth** |

1 250 500



|  |
| --- |
| **Agent4Edu** |

1 250 500

 Agent4Edu Win Tie Agent4Edu Lose

**(b)** **(c)**

0.7

12.33%



**Agent4Edu**

黑

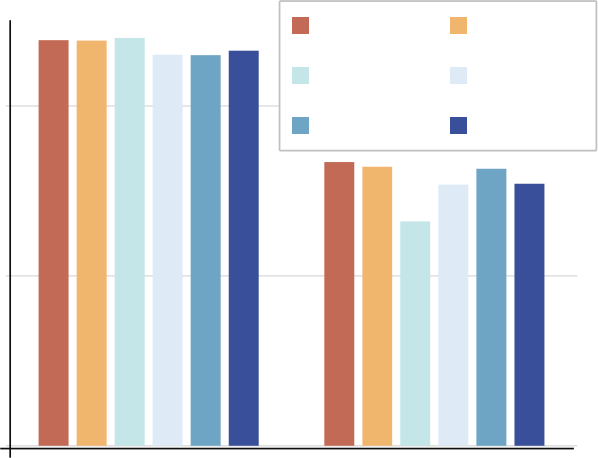
**Human**

0.5

37.33%

42.67%

**Answering** **Summarization**

complete w/o mem w/o fgt

w/o prof w/o enh w/o ref

**Knowledge** **Pre.** **Response** **Pre.**

Figure 2: (a) Comparison between the success rate distributions of ground-truth and agent-simulated response data. (b) Using LLMs as judges to identify whether the records of the agent’s simulations originate from real humans. (c) The ablation studies.

Success Rate Success Rate

ACC

23.00%

45.00%

39.67%

**Agent4Edu**

0.6

**Human**

Table 2: The ACC of knowledge prediction.

|  |  |
| --- | --- |
| Model | ACC ↑ |
| Agent4Edu (GPT-3.5-turbo) | 73.88 |
| Agent4Edu (GPT-3.5-turbo)100 | 74.57 |
| Agent4Edu (GPT-4)100 | 82.43 |

concept from this list based on its understanding (detailed prompts are provided in Appendix C). We use ACC as the metric to evaluate the agent’s knowledge predictions for all exercises in the test set, treating it as a binary classifica- tion task. This section uses the same agents from the section “Learner Simulation Evaluation”. The experimental results presented in Table 2, indicate that all the agents can cor- rectly identify the knowledge being tested in most practice exercises. This demonstrates the strong human-like ability and rich knowledge of LLMs to comprehend exercises. Fur- thermore, under the same conditions with 100 learners, the agent with GPT-4 is more accurate than the one with GPT- 3.5-turbo, indicating that GPT-4 has a stronger semantic un- derstanding ability compared to GPT-3.5-turbo.

**Zero-shot** **Simulation** Zero-shot simulation presents a significant challenge in real-world applications, particularly when learners are in a cold-start situation where their re- sponse data is unavailable. This limitation restricts the ap- plicability of previous simulation models. To validate the zero-shot simulation capability of the agent, we initial- ize 10 agents with randomly generated profiles and have them sequentially answer 10 randomly selected exercises with IDs {120, 250, 113, 1330, 568, 1881, 771, 593, 1, 595}. In this zero-shot scenario, we disable the corrective reflec- tion mechanism and tools, due to the absence of learner response data. The summary reflection remains usable for the agent. Three GPT-3.5-turbo models, with a temperature parameter of 0.5, act as annotators, tasked with evaluating whether each simulated record (including exercise answers and practice summaries) is written by a real human. Records deemed to be human-written are labeled as “Agent4Edu Win”, non-human records are labeled as “Lose”, and am- biguous records are labeled as “Tie”.

Table 3: Multifaceted evaluations of CAT strategies.

|  |  |  |  |
| --- | --- | --- | --- |
| Model | satisfaction | AoD | gain |
| FSI | 39 | **70** | **48** |
| KLI | 39 | 66 | 43 |
| MAAT | **42** | 68 | 45 |

The results depicted in Figure 2 (b) indicate that the agent’s performance in summarization is closely aligned with the real human responses, making differentiation be- tween the two challenging. However, the agent exhibits cer- tain limitations in answering exercise tasks compared to summarization tasks, primarily due to the complexity of rea- soning required to solve exercises.

**Ablation** **Study** We conduct ablation studies to evaluate the impact of key components within the GPT-3.5-turbo- powered agent. The results illustrated in Figure 2 (c) show the accuracy of the agent’s exercise-related knowledge pre- diction and response prediction under various conditions: without the profile module (w/o prof), without the memory module (w/o mem), without the memory enhancement (w/o enh), without the memory forgetting (w/o fgt), and without reflection (w/o ref). These findings confirm the effectiveness of each component in improving the agent’s predictive per- formance on learners’ response data. However, the ablation experiments indicate that the impact on knowledge predic- tion is not significant. This can be attributed to the fact that the original GPT-3.5-turbo model already possesses a sub- stantial amount of knowledge, which is sufficient to support exercise comprehension.

**4.2** **Personalized** **Learning**

***Motivation*** The primary objective of Agent4Edu is to comprehensively and accurately evaluate personalized learning algorithms and use the generated data to enhance their effectiveness. We aim to validate this objective from two perspectives: (1) through an agent-based multifaceted evaluation of personalized learning services, and (2) by as- sessing the potential improvements in personalized learning algorithms based on the simulated data.

**Multifaceted** **Evaluation** Human learners have multi- faceted evaluations of different personalized learning ser- vices, such as whether the recommended task difficulty is too challenging. Assuming that a generative agent can ac- curately simulate the behavior of real learners, its evalua- tion of personalized algorithms tends to align with human evaluations. We utilize the Computerized Adaptive Testing (CAT) which aims to estimate learners’ ability or knowledge proficiency with minor exercises, as the experimental envi- ronment, including FSI (Lord 2012), KLI (Chang and Ying 1996), and MAAT (Bi et al. 2020). We use 100 randomly initialized agents to generate virtual data for pretraining the cognitive diagnosis model (i.e., the IRT model (Baker 2001)) in the CAT algorithm for learner evaluation. Based on this, each adaptive algorithm iterates through 10 rounds to rec- ommend 100 randomly initialized agents (zero-shot simu- lation), with one exercise recommendation per round. Upon the conclusion of personalized testing, each agent is required to evaluate each CAT algorithm. To achieve this, we design three evaluation metrics, including satisfaction, appropriate- ness of difficulty (AoD), and whether there was any gain. Ta- ble 3 presents a comprehensive evaluation of various strate- gies, where the element in the i-th row and j-th column rep- resents the number of agents that consider the correspond- ing CAT algorithm i to meet the metric j. Clearly, the agent demonstrates higher satisfaction in recommending MAAT. This observation aligns with the common understanding in the research community that MAAT considers both the dif- ficulty of exercises and the diversity of knowledge (Bi et al. 2020), making the overall service more reasonable. Addi- tionally, FSI focuses on recommending exercises that are moderately difficult and likely to provide gain. These find- ings highlight the LLM-powered agent’s fine-grained evalu- ation level for learning algorithms.

**Personalized** **Learning** **Algorithm** **Improvement** We investigate whether the simulated data generated by Agent4Edu can enhance personalized learning algorithms. We select CAT as our personalized learning assessment task due to their representativeness in intelligent education. If the generated data can improve the performance of CAT models, it will indicate the effectiveness of our proposed Agent4Edu.

To set up, we select 60% of the learners’ data from EduData to train the cognitive diagnosis models (i.e., the IRT model) for learner evaluation in CAT algorithms (i.e., FSI (Lord 2012), KLI (Chang and Ying 1996), and MAAT (Bi et al. 2020)). The remaining 40% of learners’ data is used to test the CAT models. Furthermore, for each learner in the test data, we simulate their responses to 20 ran- domly selected unseen exercises based on their profiles. Us- ing this strategy, we generate simulated learner data, which are then merged with the training data from the original Edu- Data to form the augmented dataset, EduData+. We train the IRT model in each CAT model using both the original Edu- Data and EduData+, and then evaluate each CAT strategy by recommending 5 and 10 test exercises for each learner.

Table 4 lists the IRT prediction performance after retrain- ing on the testing records via CAT, where F1-score repre- sents scores on EduData, and F1-score+ represents scores on

Table 4: The improvement of CAT services.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | Testing length is 5 | | | Testing length is 10 | | |
| Model | F1-score | F1-score+ | Imp. | F1-score | F1-score+ | Imp. |
| FSI | 80.11 | 82.39 | +2.28 | 81.10 | 82.51 | +1.41 |
| KLI | 79.45 | 81.84 | +2.39 | 80.63 | 82.82 | +2.19 |
| MAAT | 81.77 | 81.97 | +0.20 | 81.71 | 81.88 | +0.17 |

EduData+. The results demonstrate that CAT strategies can be effectively enhanced with the assistance of Agent4Edu. This suggests that Agent4Edu is capable of generating high- quality learner response data, even with randomly initialized agents (in zero-shot scenarios), thereby enriching the pro- vided dataset.

**5** **Conclusion**

In this paper, we introduce Agent4Edu, an innovative per- sonalized learning simulator that leverages LLM-powered generative agents to simulate learners’ response data, as well as detailed problem-solving behaviors. Our generative agents are equipped with learner Profile, Memory and Ac- tion modules specifically tailored for personalized learning scenarios. These agents exhibit human-like choosing, under- standing, analyzing and answering exercises, which accu- rately predict their future responses. Additionally, the gen- erative agent can interact with personalized learning en- vironments to evaluate and enhance intelligent services. Through comprehensive and meticulous evaluation, we ex- plore the strengths and weaknesses of Agent4Edu, empha- sizing the consistency and discrepancies in practice behav- iors observed between agents and learners. In the future, we plan to research multi-learner agent cooperation and multi- modal practice solutions using generative agents. We hope that our research will provide new insights into the field of intelligent education.

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