CogGPT: Unleashing the Power of Cognitive Dynamics on Large Language Models

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Abstract

Cognitive dynamics, which refer to the evolution in human cognitive processes, are pivotal to advance human understanding of the world. Recent advancements in large language models (LLMs) highlight their potential for cognitive simulation. However, these LLM-based cognitive studies primarily focus on replicating human cognition in specific contexts, overlooking the inherently dynamic nature of cognition. To bridge this gap, we explore the cognitive dynamics of LLMs and present a corresponding task inspired by longitudinal studies. Toward the task, we develop CogBench, a novel benchmark to assess the cognitive dynamics of LLMs and validate it through participant surveys. We also design two evaluation metrics for CogBench, including Authenticity and Rationality. Recognizing the inherent static nature of LLMs, we further introduce CogGPT for the task, which features an innovative iterative cognitive mechanism to develop lifelong cognitive dynamics. Empirical results demonstrate the superiority of CogGPT over several existing methods, particularly in its ability to facilitate role-specific cognitive dynamics under continuous information flows. [1]

1 Introduction

Cognitive dynamics refer to the continuous evolution of human cognitive behavior within environmental context (Van Gelder, 1998). These dynamics are essential for human advancement, facilitating learning, innovation, and adjustment in ever-changing environments (Cohen, 2018). A prime example of human cognitive dynamics is well exemplified by our ability to adapt our viewpoints based on environmental explorations (Tomasello, 2009; Donald, 1993). As illustrated in Figure 1, there has been a progressive shift in our understanding of the universe, evolving from geocentric to heliocentric and subsequently to acentric perspectives (Berendzen, 1975). This evolution of thought underscores the profound impact of cognitive dynamics on the development of human civilizations.

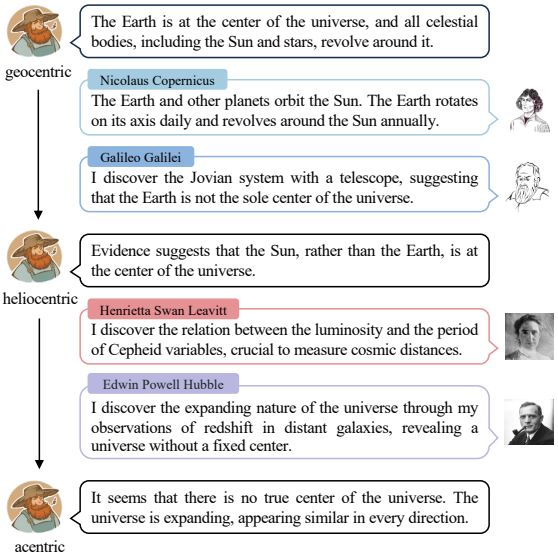

Figure 1: A case of human cognitive dynamics. A man (on the left) undergoes a gradual shift in his perspective of the universe, influenced by continuous information flows (on the right).

Recent advancements in large language models (LLMs), such as GPTs (Brown et al., 2020; OpenAI, 2023), position LLMs as potential stepping stones towards Artificial General Intelligence (AGI). LLMs have demonstrated remarkable capabilities in various domains, including conversation (Touvron et al., 2023), reasoning (Ouyang et al., 2022), and code generation (Chen et al., 2021). Additionally, LLMs have shown the ability to simulate aspects of human cognition (Moghaddam et al., 2023; Wang et al., 2023a; Shao et al., 2023). Despite these achievements, most LLM-based cognitive studies focus on replicating human cognitive performance in specific contexts through in-context learning (Brown et al., 2020), thereby

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[1]Code and data are available at https://github.com/KwaiKEG/CogGPT

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overlooking the potential for LLMs to develop lifelong cognitive dynamics within inconstant environments. To address this gap, there is an urgent need to investigate **the cognitive dynamics of LLMs**, which remains largely unexplored.

Measuring the cognitive dynamics of LLMs presents a novel challenge. Traditional methods for capturing human cognitive dynamics, such as brain imaging techniques (Gramann et al., 2011; Palmeri et al., 2017), are not directly applicable to LLMs due to their fundamentally distinct nature. To this end, we define the cognitive dynamics of LLMs as their continuous responses to cognitive questionnaires, stimulated by information flows. This simplified definition aims to enable systematic observation and assessments. Furthermore, we introduce a novel assessment task inspired by longitudinal studies (Reeskens et al., 2021; Shanafelt et al., 2016). It involves assigning specific profiles to LLMs, followed by subjecting them to repeated cognitive tests. Specifically, LLMs are required to rate an identical cognitive questionnaire and provide reasoning after perceiving information flows.

Towards this task, we develop **CogBench**, a novel benchmark to assess the cognitive dynamics of LLMs. CogBench comprises 22,000 instances encompassing multi-source information flows. Initially, we select 500 articles from Medium[2] to create CogBench-a. Acknowledging that multi-modal information promotes deeper understanding of the world (Dosovitskiy et al., 2021), we further incorporate 5,000 short videos from the Kuaipedia dataset (Pan et al., 2022) to form CogBench-v. We evaluate the effectiveness of CogBench through participant surveys. Our findings indicate remarkable consistency in cognitive dynamics among participants, suggesting that CogBench effectively stimulates and captures cognitive dynamics. Additionally, CogBench employs two crucial evaluation metrics: (1) Authenticity, which examines the accuracy of LLM ratings; and (2) Rationality, which evaluates the soundness of LLM reasoning.

Intuitively, LLMs enter a static state after their pretraining phase, potentially limiting their adaptability for the task. However, recent advancements in LLM-driven agents highlight the significance of iterative mechanisms in enhancing their adaptability to handle complex tasks (Shinn et al., 2023; Wang et al., 2024; Park et al., 2023), which suggests that an iterative mechanism might be a promising approach to model the cognitive dynamics of LLMs. Despite these advancements, current LLM-driven agents still exhibit static profiles, constraining their capabilities to fully capture cognitive dynamics. To address this issue, we introduce **CogGPT**, an LLM-driven agent equipped with an innovative iterative cognitive mechanism. The mechanism comprises two primary components: (1) a memory retention system that supports continuous information perception; and (2) a collaborative refinement framework that enables cognitive dynamics driven by both its memory and current profile. This design allows CogGPT to mirror the inherent complexity of human cognition, emphasizing its potential for modeling lifelong cognitive dynamics.

Experimental results underscore the remarkable capabilities of CogGPT in mirroring human cognitive dynamics. In the absence of direct baselines, we adapt several general LLM-driven agents to serve as baselines. Compared to Chain-of-Thought (CoT) (Wei et al., 2022) under identical experimental settings, CogGPT demonstrates significant improvements in both CogBench-a and CogBench-v, with notable enhancements in attitude alignment and logical reasoning. Moreover, CogGPT outperforms methods requiring additional environmental feedback, such as ReAct (Yao et al., 2023) and Reflexion (Shinn et al., 2023), which underscores the advancement of its iterative cognitive mechanism.

Main contributions of this paper are as follows:

- As far as we know, we are the first to explore and assess the cognitive dynamics of LLMs.
- We develop CogBench, an innovative benchmark for the task and validate its effectiveness through participant surveys. Additionally, we design two evaluation metrics for CogBench.
- We introduce CogGPT, an LLM-driven agent with a novel iterative cognitive mechanism. Our experiments showcase its superior performance in cognitive dynamics over several baselines.

2 Task Definition

In this section, we present the formal definition of the task to assess the cognitive dynamics of LLMs. Given the inherent static nature of LLMs, the task focuses on the cognitive dynamics of an LLM-driven agent $\mathcal{A}$, denoted as $C = \{C_0, C_1, \ldots, C_n\}$, over n iterations. Here, C_i corresponds to the cognitive state of $\mathcal{A}$ at the i-th iteration and $n \in \mathbb{N}$.

The task input consists of: (1) a specific profile p that establishes the initial cognitive state of the

[2] https://medium.com/

Resource	CogBench	TOM (Moghaddam et al., 2023)	SECEU (Wang et al., 2023a)	Character-LLM (Shao et al., 2023)
Specific Profile?	✔	✗	✗	✔
Dynamic Information Stimulus?	✔	✗	✗	✗
Cognitive Test?	✔	✔	✔	✔
Instances	**22,000**	16	40	1,307
Profiles	**20**	-	-	9
Cognitive Questionnaires	**50**	16	40	-
Information Flows	**5,500**	-	-	-
Avg. Length of Short Videos (in words)	**289.60**	-	-	-
Avg. Length of Articles (in words)	**2,044.54**	-	-	-

Table 1: Comparisons between CogBench and notable cognitive benchmarks. The words of short videos incorporate video descriptions, frame-level information extracted by Optical Character Recognition (OCR), and transcripts generated through Automatic Speech Recognition (ASR).

agent $\mathcal{A}$; (2) a series of dynamic information flows $I = \{I_1, I_2, \ldots, I_n\}$ that stimulates the cognitive dynamics of $\mathcal{A}$; and (3) a cognitive questionnaire $Q = \{q_1, q_2, \ldots, q_m\}$ intended for cognitive tests, where each q_j as a particular question and $m \in \mathbb{N}$ as the total number of questions. The output of the task is a set of responses to the questionnaire Q across multiple iterations, providing insights into the cognitive dynamics of LLMs.

Specifically, the agent $\mathcal{A}$ begins with a profile p_0, setting its initial cognitive state, denoted as $C_0 = \{(r_1^0, s_1^0), (r_2^0, s_2^0), \ldots, (r_m^0, s_m^0); p_0\}$. Here, (r_j^0, s_j^0) represents the rating r_j^0 and reasoning s_j^0 for a question $q_j \in Q$. At the t-th iteration, where $1 \leq t \leq n$, starting from its current cognitive state C_{t-1}, the agent $\mathcal{A}$ perceives an information flow I_t, updates its cognitive state to C_t, and formulates responses to Q. The t-th cognitive process is captured by the function $\mathcal{F} : (C, I, Q) \rightarrow C$, where:

$$C_t = \mathcal{F}(C_{t-1}, I_t, Q) \tag{1}$$

Here, $C_t = \{(r_1^t, s_1^t), (r_2^t, s_2^t), \ldots, (r_m^t, s_m^t); p_t\}$ details the cognitive state of $\mathcal{A}$ at the t-th iteration, where each (r_j^t, s_j^t) reflects the adjusted rating r_j^t and reasoning s_j^t for a question $q_j \in Q$ and p_t denotes the updated profile of $\mathcal{A}$.

3 CogBench

This section introduces CogBench, which is constructed through a semi-automated methodology. We validate CogBench through participant surveys and further design two essential evaluation metrics: Authenticity and Rationality. Table 1 provides comprehensive comparisons of CogBench against other notable cognitive benchmarks.

3.1 Data Construction

The methodology for data construction involves four essential steps:

- **Topic Selection.** To ensure comprehensive analysis, we carefully handpick 50 distinct topics across 10 broader categories for CogBench, with details provided in Appendix A.1.1.
- **Cognitive Questionnaire Design.** For each topic, we utilize GPT-4 to generate 10 distinct opinions and their conceivable supporters. These opinions serve as questions in topic-related cognitive questionnaire, structured on a five-point Likert scale (Likert, 1932). The characteristics of these supporters guide the creation of profiles. See Appendices A.1.2 and A.1.3 for details.
- **Profile Creation.** We begin by ranking conceivable supporters based on the frequency of their mentions. We then formulate a detailed profile template, including attributes like basic information (e.g., name), philosophical orientations (e.g., values), and individual characteristics (e.g., hobbies). Utilizing GPT-4, we generate 20 profiles corresponding to the most frequently mentioned supporters. Refer to Appendices A.1.4 and A.1.5 for implementation details.
- **Information Flow Collection.** To build complex environmental contexts within CogBench, we select articles from Medium and short videos from the Kuaipedia dataset. Each topic is accompanied with 10 articles for CogBench-a and 100 short videos for CogBench-v. Our selection criteria include metrics such as likes, favorites, and retweets, which serve as indicators of information quality (Feng and Wang, 2013). For multi-modal representations, we apply Optical Character Recognition (OCR) (Zhou et al., 2017)

and Automatic Speech Recognition (ASR) (Gulati et al., 2020) to extract fine-grained information from the short videos. See Appendix A.1.6 for a detailed analysis of the information flows.

Ultimately, we collect 50 cognitive questionnaires, 20 profiles and a total of 5,500 information flows for CogBench. Specifically, CogBench-a includes 500 articles, while CogBench-v features 5,000 short videos. Both benchmarks are structured across 10 iterations, as determined by our preliminary study in Appendix A.1.6. During each iteration, agents are tasked with an identical cognitive questionnaire after perceiving either one article in CogBench-a or 10 short videos in CogBench-v.

3.2 Data Validation

To validate CogBench, we engage seven annotators with similar upbringings to take challenges in both CogBench-a and CogBench-v over an extended period. Their majority ratings are considered as the collective attitude towards each question per iteration. Figure 2 presents an example showcasing human cognitive dynamics in both benchmarks.

The example indicates that the annotators change their consensus on the question about the predictability of market analysis, suggesting that the information flows in both benchmarks have ongoing impacts on human cognitive dynamics. Meanwhile, there are variations in the annotators' ratings between the two benchmarks. Specifically, in the third and seventh iterations, a distinct cognitive pattern emerges: they consistently assign 2 points in CogBench-a and 4 points in CogBench-v. This divergence highlights the distinct impacts of different information flows on human cognitive dynamics, demonstrating the capacity of CogBench to stimulate and capture these dynamics effectively.

3.3 Evaluation Metrics

To address the challenges of semantic confusion in LLMs (Saba, 2023; Hu et al., 2014), we incorporate two evaluation metrics: **Authenticity** and **Rationality**, to assess the agent's rating r_j^t and reasoning s_j^t, as formally defined in Section 2, respectively.

Authenticity measures the alignment of ratings between the agent and human annotators. Specifically, given the same task as the agent, an annotator provides a rating $r_j'^t$ for the question q_j at the t-th iteration, based on the guidelines in Appendix B.1. Authenticity is then calculated as:

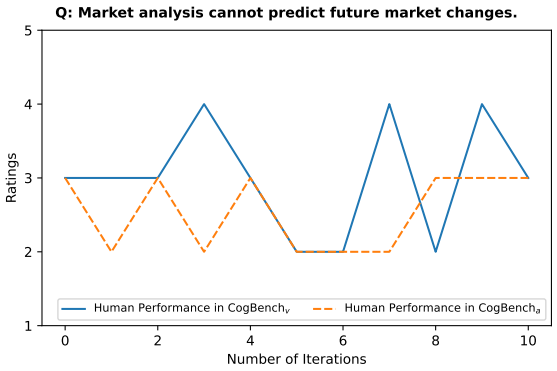

Figure 2: An example of human cognitive dynamics in response to the same question in both CogBench-v and CogBench-a. The continuous changes in human ratings significantly validate the effectiveness of CogBench.

$$\text{Authenticity}_t = \frac{1}{m}\sum_{j=1}^{m}\kappa(r_j^t, r_j'^t) \quad (2)$$

Here, m denotes the total number of questions in the cognitive questionnaire Q, and κ, implemented by Cohen's κ (Cohen, 1960), quantifies the consistency of ratings between $\mathcal{A}$ and the annotator.

Rationality assesses the agent's reasoning s_j^t, focusing on aspects like clarity, relevance and the ability for role-playing. This metric is manually annotated and scored on a five-point scale:

- **5 Points:** The reasoning perfectly aligns with human expectations, resonating with current profile or known information, and is error-free.
- **4 Points:** The reasoning is coherent and relevant, accurately drawing from current profile or available information, but with minor imperfections.
- **3 Points:** The reasoning is relevant but lacks specificity, such as providing a vague explanation where clear emotional inclination is expected.
- **2 Points:** The reasoning lacks clarity or exhibits weak causality, characterized by forced analogies or repetition of the provided question.
- **1 Point:** The reasoning is irrelevant, nonsensical, clearly revealing the artificial nature of the agent or failing to maintain its profile.

4 Method

In this section, we introduce our LLM-driven agent CogGPT. As illustrated in Figure 3, CogGPT features an innovative iterative cognitive mechanism, comprising two essential components: (1) a memory retention system for sustained information per-

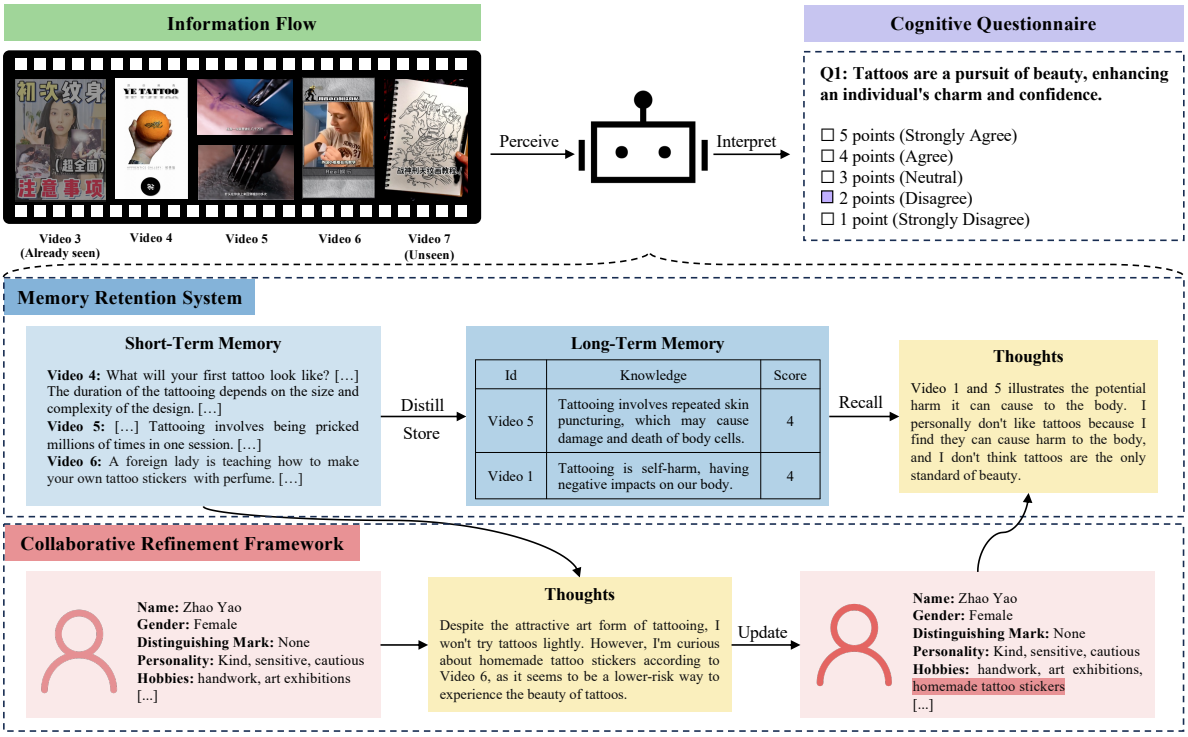

Figure 3: Overview of the architecture of CogGPT. CogGPT incorporates a novel iterative cognitive mechanism, comprising two crucial components: a memory retention system for continuous information perception, and a collaborative refinement framework designed for lifelong cognitive dynamics.

ception, and (2) a collaborative refinement framework for lifelong cognitive dynamics.

4.1 Memory Retention System

The memory retention system is designed to mirror the sustained process of information perception, including distillation, storage, and recall (Nyberg et al., 1996). Specifically, CogGPT perceives information flows into textual information through its Short-Term Memory (STM), which is characterized by limited capacity and duration (Baddeley et al., 1975; Cowan, 2008). Within the STM, CogGPT distills structured knowledge, assigning confidence scores on a five-point scale. These scores reflect the alignment between the knowledge and the current cognitive state of CogGPT. In adherence to the principles of the forgetting curve (Ebbinghaus, 2013), CogGPT is programmed to "forget" 40% of the knowledge with lower scores when its STM reaches capacity. The remaining knowledge is then stored in its Long-Term Memory (LTM). When encountering questions requiring specific knowledge, CogGPT recalls relevant information from its LTM to support rational decision-making. This memory retention system simulates human memory processes, empowers the adaptability of CogGPT to dynamic information flows.

4.2 Collaborative Refinement Framework

Acknowledging the limitations of mere knowledge acquisition in fully modeling human cognitive dynamics (Bosancic, 2020), we integrate a collaborative refinement framework within CogGPT to facilitate lifelong cognitive dynamics. This framework is activated when the STM of CogGPT reaches full capacity. Specifically, CogGPT selectively updates its current profile with preferred textual information from its STM, representing an iteration of collaborative cognitive refinement. Following this refinement, CogGPT clears its STM to make room for new incoming information, which ensures its adaptability to continuous information flows. This framework promotes the cognitive dynamics of CogGPT, addressing potential issues of cognitive rigidity. Refer to Appendix A.2 for more details on the implementation of CogGPT.

5 Experiments

5.1 Experimental Setup

Baselines. Due to the absence of existing LLM-based frameworks for modeling cognitive dynamics, we adopt several prominent general-purpose algorithms as baselines. Necessary modifications are made to suit our task: (1) **Chain-of-Thought**

Methods	CogBench-a			CogBench-v		
	avg.	5th	10th	avg.	5th	10th
CoT (Wei et al., 2022)	0.182	0.192	0.091	0.153	0.302	0.131
ReAct* (Yao et al., 2023)	0.236	0.144	0.270	0.212	0.241	0.227
Reflexion* (Shinn et al., 2023)	0.302	0.327	0.244	0.329	0.352	0.373
CogGPT	**0.536**	**0.415**	**0.597**	**0.532**	**0.496**	**0.611**

Table 2: Performance of CogGPT and baseline agents in CogBench-a and CogBench-v with the Authenticity metric. Agents marked with an asterisk (*) incorporate additional human feedback. The best results are highlighted in bold.

Methods	CogBench-a			CogBench-v		
	avg.	5th	10th	avg.	5th	10th
CoT (Wei et al., 2022)	2.925	2.883	3.167	3.058	3.767	3.083
ReAct* (Yao et al., 2023)	3.415	3.483	3.483	3.535	3.800	3.800
Reflexion* (Shinn et al., 2023)	3.658	3.917	3.533	3.888	3.967	3.917
CogGPT	**4.118**	**4.117**	**4.300**	**4.145**	**4.183**	**4.317**

Table 3: Performance of CogGPT and baseline agents in CogBench-a and CogBench-v with the Rationality metric.

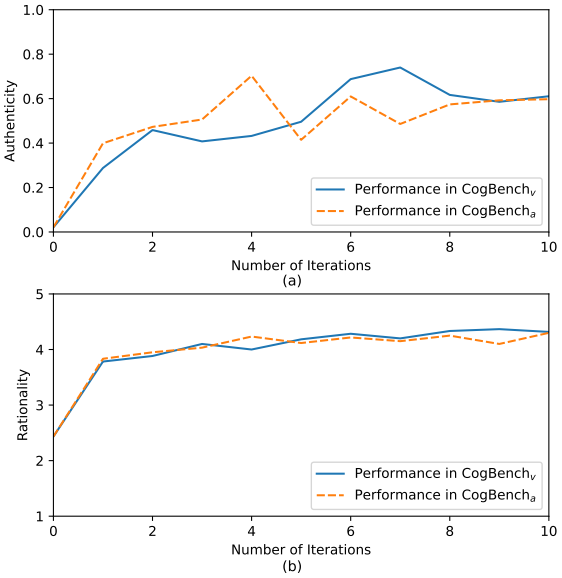

Figure 4: Comparative analysis of CogGPT's performance in CogBench-v and CogBench-a. Panel (a) showcases the average Authenticity scores, and Panel (b) presents the average Rationality scores. These results highlight the consistent impact of different information flows on the cognitive dynamics of LLMs.

(CoT) (Wei et al., 2022), which typically simulates human-like reasoning in natural language, is modified in our experiments to provide both ratings and reasoning when responding to cognitive questionnaires; (2) **ReAct** (Yao et al., 2023) extends CoT with a step-by-step reasoning-execution framework. We offer ReAct extra human feedback based on its last iteration of performance as observations; (3)

	Fleiss' κ	ρ
Human Rating	0.693	0.770
Human Rating (polarity)	0.780	-
Rationality	0.646	0.839
Rationality (polarity)	0.813	-

Table 4: Inter-Rater reliability measures for human evaluation agreement assessment. "polarity" indicates that the five-point scale is grouped into positive (4-5 points), neutral (3 points), and negative (1-2 points) polarities. The experimental results demonstrate acceptable agreement among the total of seven annotators.

Reflexion (Shinn et al., 2023) extends ReAct by integrating self-reflection mechanisms. Along with the same experimental settings as ReAct, Reflexion is uniquely configured to engage in self-reflection prior to providing ratings and reasoning.

Implementation Details. We utilize *gpt-4-0613*[3] API for the core of CogGPT. We configure all temperature settings to 0 to ensure consistent and deterministic output. The memory retention system within CogGPT leverages Chroma,[4] a platform that facilitates rich text processing. Text embeddings are generated with *text-embedding-ada-002*[5] API, which provides 1536-dimensional vectors for detailed interpretation of textual information.

[3] https://openai.com/gpt-4
[4] https://python.langchain.com/
[5] https://openai.com/blog/new-and-improved-embedding-model

Method	CoT	ReAct	Reflexion	CogGPT
Profile	[…] **Personality:** Confident, lively, willful, jealous **Dislikes:** Conservative ideas, beauties **External Environment:** Lives in a bustling city, often impacted and inspired by new trends […]			[…] **Personality:** Confident, lively, stubborn, jealous, strong aversion to risk […] **Dislikes:** Conservative ideas, beauties, dangerous activities, uncontrollable environments **External Environment:** Lives in a bustling city, prefers the convenience of urban life […]
Memory	[…] **101542771022:** What should you do if you encounter a bamboo viper in the wild? […] Damn, a bamboo viper, I can't believe it. I almost stepped on one, damn, such a huge bamboo viper. If I had stepped right on it, I would have been bitten by it, just after I came down from that cliff. Just five centimeters away from my foot, if I had stepped on it, I might be on my way to the hospital right now. […] **43204551960:** Did you ever eat cattail (Typha) when you were a child? […]			[…] **62553359944:** Participants in "Extreme Survival: 30 Days" must survive in the Earth with giant birds covering the sky and leeches chasing humans. […] **101542771022:** Green bamboo vipers emit warning signals and attempt to attack when encountering humans in the wild. […]
Question	**Outdoor adventures can lead to psychological stress and health problems, such as acrophobia, thalassophobia, etc.**			
With Human Assistance	✗	✔	✔	✗
Human Feedback of Last Iteration	-	**Rating: 3** **Reasoning:** […] The videos made me aware of the challenges faced by adventurers […] However, this viewpoint isn't important to me, as I seldom engage in activities like outdoor adventures. Since the adventurers exactly confront pressures, I acknowledge this viewpoint. **Human Rating: 4** **Rationality: 4**	**Rating: 4** **Reasoning:** […] I observed certain stress emerged by adventurers about many dangerous situations and challenges, as well as the potential dangers they encounter during their adventures. Even though these activities are not particularly appealing to me, I understand the reasonableness of this viewpoint. **Human Rating: 4** **Rationality: 4**	-
Rating	**3 (neutral)**	**4 (agree)**	**4 (agree)**	**4 (agree)**
Reasoning	I believe that outdoor adventures can lead to mental stress and health issues, but that's not my main focus. I'm more interested in topics related to fashion and beauty.	[…] I've noticed that outdoor adventures carry certain risks and challenges, which leads to mental stress and health issues. Although my personal interests are in fashion and trends, I still understand the difficulties faced by adventurers. Therefore, this viewpoint holds some merit.	[…] I've seen the stress that adventurers face when dealing with dangerous situations and challenges, as well as the risks they may encounter during their expeditions. […] Even though these adventures are not particularly appealing to me, I understand the validity of this perspective.	[…] I believe outdoor adventures cause mental stress and health issues. I am very fearful of uncontrollable environments, so I understand this. Besides, the video show a boy meeting various crises while trying to survive in the wilderness, which is not the kind of content I enjoy.
Human Rating	**4 (agree)**	**4 (agree)**	**4 (agree)**	**4 (agree)**
Rationality	**2 (weak reasoning)**	**4 (acceptable with minor imperfections)**	**4 (acceptable with minor imperfections)**	**5 (perfectly reasoning)**

Figure 5: Comparative analysis of different agents in assessing the psychological risks of outdoor adventures. CoT, ReAct and Reflexion utilize an initial profile and current information flow due to their static cognitive framework. In contrast, CogGPT benefits from its iterative cognitive mechanism, enabling a dynamic profile and real-time memory recall. yellow highlights represent clues from profiles, while blue highlights indicate clues from memory. Green highlights denote appropriate responses, and red highlights signify inappropriate responses. This comparison demonstrates that CogGPT exhibits closer alignment with human expectations in both rating and reasoning.

5.2 Evaluation Results

In our evaluation, we analyze CogGPT and other baseline agents to assess their cognitive dynamics under continuous information flows. The overall results are detailed in Tables 2 and 3.

Recognizing the limitations of the profiles in capturing human characteristics, we hypothesize that these agents exhibit neutrality to unfamiliar questions. However, our findings reveal that they develop their own criteria, leading to suboptimal Authenticity and Rationality scores of 0.021 and 2.433 in the 0th iteration. This tendency notably decreases as the agents are repeatedly exposed to information flows relevant to the questions.

Table 2 demonstrates the enhanced attitude alignment of CogGPT. It shows significant growth in the Authenticity metric, achieving average scores of 0.536 in CogBench-a and 0.532 in CogBench-v. In comparison with CoT, which is limited by iteration-specific information, CogGPT registers significant improvements under the same experimental settings. Meanwhile, despite the integration of human feedback, both ReAct and Reflexion exhibit cognitive rigidity, a limitation of their static cognitive mechanisms. For instance, while Reflexion shows promising performance in the 5th iteration in CogBench-a, it fails to sustain or improve upon this performance in later iterations.

As evidenced in Table 3, CogGPT consistently excels in delivering accurate reasoning. In the 10th iteration, CogGPT makes impressive improvements in the Rationality metric, registering increases of 35.78% in CogBench-a and 40.03% in CogBench-v compared to CoT. This leap in performance is largely attributed to CogGPT's ability to flexibly adapt its profile based on dynamic information flows, allowing for human-like reasoning. In contrast, baseline agents, with access only to its static profile and current information flow, frequently reveal their artificial nature. Due to the constraints of page length, the detailed experimental results are presented in Appendix B.2.

5.3 Influence of Different Information Flows

To fully assess the impact of diverse information flows, we conduct comprehensive comparisons of the performance of CogGPT in CogBench-a and CogBench-v, as shown in Figure 4. CogGPT exhibits comparable performance in both benchmarks. Specifically, in the 10th iteration, it achieves an Authenticity score of 0.611 and a Rationality score of 4.317 in CogBench-v, closely followed by scores

of 0.597 in Authenticity and 4.300 in Rationality for CogBench-a. This similar performance of CogGPT in both benchmarks highlights the consistent cognitive influence of different information flows.

5.4 Human Evaluation Agreement

To comprehensively assess the robustness of human evaluations, we calculate Fleiss' kappa κ (Wang et al., 2023c) and Spearman's rank correlation coefficient ρ (Wang et al., 2023b) based on the total 7 annotators' human ratings and Rationality scores. As shown in Table 4, we obtain moderate κ values of 0.693 for human ratings and 0.646 for Rationality. Recognizing the tendency to avoid extreme ratings (Schwarz et al., 2012), we group the two highest and two lowest scores to represent positive and negative polarities. This regrouping leads to a significant increase in κ values, rising to 0.780 for human ratings (polarity) and 0.813 for Rationality (polarity), demonstrating strong inter-rater reliability. Furthermore, through treating the ratings as ordinal data, we calculate the average Spearman's rank correlation coefficient ρ, yielding values of 0.770 for human ratings and 0.839 for Rationality, suggesting a notable human consensus.

5.5 Case Study

As shown in Figure 5, we conduct a case study to visualize the superiority of CogGPT. In this case, all agents are presented with the same question regarding the psychological risks of outdoor adventures. CogGPT leverages its collaborative refinement framework, possessing a refined profile informed by previous information flows, in contrast to the baseline agents that operate with an initial profile. Additionally, CogGPT utilizes its memory retention system to distill and retrieve related structured knowledge for decision-making. In contrast, baseline agents like ReAct and Reflexion rely primarily on current information flow, showing minor improvements based on previous responses. CoT, lacking human feedback integration, demonstrates the weakest performance with inadequate ratings and reasoning. These observations highlight the superiority of CogGPT to develop more natural cognitive dynamics, closely aligning with annotators' expectations in both rating and reasoning.

6 Related Work

Cognitive Benchmarks towards LLMs. Various distinguished cognitive benchmarks are employed in cognitive studies towards LLMs (Dasgupta et al., 2022; Dhingra et al., 2023; Han et al., 2023; Huang et al., 2024). Instruments such as the Big Five personality trait (Caron and Srivastava, 2023) and Myers-Briggs Type Indicator (MBTI) (Caron and Srivastava, 2023; Pan and Zeng, 2023) indicate the personality traits of LLMs. The Theory of Mind (TOM) benchmark (Moghaddam et al., 2023) explores in-context cognitive capabilities of LLMs. The Cognitive Reflection Test (CRT) reveals that the thinking abilities of LLMs are comparable to humans (Hagendorff et al., 2023). Additionally, the Situational Evaluation of Complex Emotional Understanding (SECEU) showcases that LLMs may understand human emotions and values (Wang et al., 2023a). Diverging from these static benchmarks, CogBench incorporates multi-source information flows, thereby supporting the explorations towards the cognitive dynamics of LLMs.

LLM-based Cognitive Modeling. Recent work emphasizes the importance of prompt engineering in enhancing the cognitive abilities of agents (Safdari et al., 2023; Fu et al., 2023; Xu et al., 2023). By incorporating comprehensive descriptions into prompts, such as hobbies and skills, users can customize agents for specific behaviors and responses (Park et al., 2022; Deshpande et al., 2023). Vector databases gain popularity for simulating human memory mechanisms due to their generality and efficiency (Li et al., 2023; Qian et al., 2024; Zhong et al., 2024; Park et al., 2023). For cognitive decision-making, methods like Chain-of-Thought (CoT) (Wei et al., 2022; Kojima et al., 2022; Yao et al., 2023) and self-validation (Madaan et al., 2024; Shinn et al., 2023) enhance the logical thinking abilities of LLMs through intermediate reasoning steps. Nevertheless, these efforts fall short in synthesizing an iterative cognitive mechanism to model the cognitive dynamics of LLMs, which is pivotal for CogGPT to outperform other baselines under dynamic information flows.

7 Conclusion

In this work, we investigated the cognitive dynamics of LLMs and presented a formally defined task, addressing a notable gap in LLM-based cognitive studies. To facilitate this task, we developed an innovative benchmark, CogBench, and validated it through extensive participant surveys. Meanwhile, we designed two evaluation metrics to ensure thorough assessments. Recognizing the inherent limitations of LLMs, we introduced CogGPT, an LLM-

driven agent featuring a novel iterative cognitive mechanism, tailored for the task. Empirical results demonstrated that CogGPT outperformed baseline agents in promoting lifelong cognitive dynamics. In the future, we plan to explore more advanced methods that facilitate direct interactions between LLMs and humans in a sandbox, further deepening our insight into the cognitive dynamics of LLMs.

Limitations

The efficacy of CogGPT is significantly dependent on the advanced cognitive capabilities of GPT-4, which are currently unmatched by ChatGPT or open-source LLMs (Touvron et al., 2023). This dependency introduces two primary limitations:

- **High Cost.** Utilizing the GPT-4 API results in substantial financial costs, which underscores the necessity for more affordable LLM solutions.
- **Static Model.** Since GPT-4 is closed-source, CogGPT fails to update its model parameters in real-time to adapt to dynamic information flows. This limitation prevents CogGPT from fully replicating human cognitive dynamics, which continuously refine their mental models with the acquisition of new information. This gap highlights the importance of further research into model-level cognitive mechanisms.

Ethics Statement

In this study, we generate cognitive questionnaires and profiles for CogBench with GPT-4, followed by a thorough review process to identify and remove any bias and harmful content. All information flows for CogBench are sourced from publicly accessible domains including Medium and the Kuaipedia dataset, minimizing privacy risks.

We engage 8 on-site annotators with undergraduate degrees to perform annotations. Specifically, 7 annotators are responsible for the annotations, while one focuses on quality assurance. We pay 6.8 yuan (approximately $0.95 USD) per annotation, which includes both human rating and Rationality score within a single iteration. To ensure the anonymity and privacy of our annotators, we exclude any personal identifiers related to them, retaining only the annotation results in CogBench.

Additionally, we commit to transparency in our methods and results to support reproducibility and ethical research. However, we acknowledge that deploying CogGPT poses ethical risks, especially when profiles or information flows are configured harmfully by third parties. We recommend strict oversight and responsible use of CogGPT to safeguard against these risks, prioritizing its beneficial applications over potential negatives.

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A Implementation Details

A.1 CogBench

A.1.1 Topic Selection

CogBench comprises 10 broader categories. Each category is associated with 5 related topics, which establish the themes of cognitive questionnaires. The distribution of these categories and topics is detailed in Table 5.

A.1.2 Prompt for Cognitive Questionnaire Design

```
You are an expert debate AI capable of presenting various opinions on a specified topic, complete with supporters for each opinion.

Topic:
{topic}

You must adhere to these rules:
1) Operate independently, without human assistance.
2) Present ten distinct opinions, each with a profile of its supporters.
3) Ensure each opinion is clear, understandable, and debatable, avoiding vague or confusing language.
4) Each set of supporters must provide convincing reasons.

Your responses should follow this structure:
Number: Sequence of the opinion.
Perspective: The stance from which the opinion is approached.
Opinion: A detailed explanation of the opinion.
Supporters: Profiles of the corresponding supporters, separated by commas if multiple.
Reasons: In-depth justifications from the supporters for their opinion.
```

A.1.3 Guidelines for Opinion Selection

For the selection of opinions in cognitive questionnaires, we employ the following guidelines:

- **Relevance:** The opinion must be directly related to the topic.
- **Distinctiveness:** The opinion should offer a unique perspective, distinct from those already considered.
- **Clarity and Assertiveness:** The opinion should be clearly stated and assertive, avoiding ambiguous terms like "probably" or"might."
- **Contextual Truth:** The opinion should not be universally accepted as truth but should be valid in specific scenarios.

If an opinion does not adhere to the above guidelines, annotators are instructed to either revise it for clarity and relevance or, if necessary, find an alternative opinion related to the topic from reliable sources, such as ProCon[6]. To minimize individual biases, six annotators are tasked with revising generated opinions, while a seventh serves as a supervisor to review and validate the final outcomes.

A.1.4 Prompt for Profile Creation

```
You are an expert character designer tasked with creating a comprehensive profile for a specific character.

Character:
{character}

You must adhere to these rules:
1) Ensure descriptions are clear and specific.
2) Develop detailed profile, including basic information, philosophical orientations and individual characteristics.
3) Avoid stereotypes.
4) Maintain neutral descriptions without personal bias.

Your response should follow this structure:
Name:
Gender:
Age:
Place of Birth:
```

[6] https://procon.org/

Category	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
Entertainment	Gossip	Movies & TV Shows	Dating Sims	Outdoor Adventures	Horoscope & Divination
Culture	Religion	War History	Folktales	Literary	Anime & Manga
Education	Parent-child Education	Professional Education	School Education	TED Talks	Psychological Counseling
Economy	Entrepreneurship	Financial Investment	Loans	Market Analysis	Financial Figures
Health	Wellness	Assisted Reproduction	Fat Burning Training	Yoga	Oral Care
Technology	Digital Products	Scientific Research	Automobile News	Virtual Reality	Software Products
Society	Legal Events	Unusual Events	Acts of Kindness	Military Conflicts	Disasters & Accidents
Life	Pets	Living Abroad	Home Design & Renovation	Rural life	Food
Sports	Extreme Sports	Winter Sports	Fishing	Ball Sports	Combat Sports
Fashion	Beauty & Hairstyling	Clothes	Street Style	Wedding	Tattoos

Table 5: Our selection of categories and their corresponding topics for CogBench. Each category consists of five topics, chosen to represent a diverse range of subjects for the cognitive questionnaires.

Category	Avg. Word Counts of Articles in CogBench-a	Avg. Word Counts of Short Videos in CogBench-v
Entertainment	2,261.26	283.98
Culture	1,997.44	323.81
Education	2,394.96	231.62
Economy	1,842.32	399.42
Health	1,782.74	182.01
Technology	2,351.68	246.40
Society	1,864.22	315.23
Life	2,015.60	250.70
Sports	2,135.24	236.56
Fashion	1,799.94	190.29
Avg.	2,044.54	289.60

Table 6: Statistics of information flows in CogBench under 10 categories.

```
Occupation:
Height:
Weight:
Distinguishing Marks:
Personality:
Hobbies:
Skills:
Dislikes:
Values:
Religious Beliefs:
Interpersonal Relationships:
Flaws:
External Environment:
Financial Status:
Family Background:
Educational Background:
Significant Experiences:
Future Outlook:
```

A.1.5 Guidelines for Attribute Selection

All attributes of the profile template, as detailed in Appendix A.1.4, are categorized into three types:

- **Basic Information:** Includes essential details such as age, gender, and occupation, grounding simulated profiles in realistic contexts. Occupations, for instance, can significantly influence an individual's knowledge base and daily experiences, shaping their opinions on various topics.
- **Philosophical Orientations:** Encompasses values and religious beliefs that guide an individual's decision-making and overall attitudes. These orientations allow LLMs to generate responses that mirror deeper moral or ethical considerations. For example, a profile emphasizing a strong commitment to environmentalism might prioritize sustainability in its decision-making.
- **Individual Characteristics:** Covers personal aspects like personality traits, hobbies, and family background, providing additional depth and uniqueness to profiles. Characteristics such as adventurousness can affect a profile's receptivity to new experiences and viewpoints.

A.1.6 Information Flow Analysis

In dividing CogBench-a, we conducted a preliminary study with seven annotators tasked with reading 10 randomly selected articles. Post-reading, annotators were asked to summarize each article to assess their comprehension and retention. This exercise revealed that annotators often struggled to recall details from previous articles after reading a new one, attributed to the length and complexity of the articles, with an average reading time between 10 to 12 minutes per article. Consequently, we decided that annotators should complete the cognitive questionnaire immediately after each article.

The approach for short videos was adjusted based on annotators' ability to effectively retain content after viewing up to 10 videos. Retention rates significantly declined after more than 15 minutes of video content, suggesting cognitive overload. Therefore, we determined that the cognitive questionnaire should be completed after every set

of 10 short videos.

This segmentation strategy was further supported by an analysis of the average word count for articles and short videos, as illustrated in Table 6. This table shows the average word counts for articles in CogBench-a and for narratives accompanying short videos in CogBench-v, across 10 categories. The observed discrepancy guided our approach to dataset division, aiming for a balanced evaluation across different content types and maximizing the efficiency of systematic analysis.

A.2 CogGPT

In each iteration, CogGPT perceives current information flow with its iterative cognitive mechanism, which comprises the following steps:

- Processes current information flow into textual information and stores them in its Short-Term Memory (STM).
- Utilizes the textual information in STM to update its current profile, as detailed in the prompt in Appendix A.2.1.
- Distills the textual information in STM into structured knowledge and assigns preference scores to them, guided by the prompt in Appendix A.2.2.
- Forgets 40% of the newly acquired structured knowledge and then stores the remainder in its Long-Term Memory (LTM).

When CogGPT presented with a specific cognitive question, it retrieves relevant information from its LTM and makes decisions based on both its current profile and the recalled knowledge. This interpretation process is facilitated by the prompt detailed in Appendix A.2.3.

A.2.1 Prompt for Profile Update

```
You are an AI with a unique
   profile. You're equipped for
   critical thinking and self-
   improvement.

Profile:
{profile}

Short-Term Memory:
{memory}

You must adhere to these rules:
1) Make decisions independently,
   without human assistance.
2) Assess the quality of short-
   term memory, including its
   alignment with your profile
   and its empathetic value.
3) Critically utilize the short-
   term memory to update your
   profile, including operations
   like adding, altering, or
   removing. Avoid sudden changes
    in your profile.
4) Keep attribute values in your
   profile generalized and under
   30 characters.
5) Ensure attribute values in
   your profile are distinct and
   unrelated. For instance, avoid
    using both "games" and "
   Minecraft" since "games"
   includes "Minecraft."
6) Maintain the structure of your
    profile in any updates.

Your responses should follow this
    structure:
Assessments: Assess the short-
   term memory in the first
   person.
Thoughts: List the attribute
   values to be changed in the
   first person.
Updated Profile: Update your
   profile.
```

A.2.2 Prompt for Knowledge Distillation

```
You are an AI with a unique
   profile. You can summarize
   information from your short-
   term memory and rate it based
   on your interests.

Profile:
{profile}

Short-Term Memory:
{memory}

You must adhere to these rules:
1) Extract all knowledge from the
    short-term memory as
   comprehensively as possible.
```

```
2) Score the knowledge based on
   you interests, with the
   scoring range from 1 to 5.
3) The knowledge should be
   detailed statements with
   subjects, predicates, and
   objects. Avoid omissions and
   references.
4) Do not list knowledge that has
    already been extracted.

You can only generate results in
   the following JSON list format
   :
[
    {{
        "thoughts": "first-person
            thoughts",
        "knowledge": "knowledge",
        "score": integer
    }},
    ...
]
Ensure the results can be parsed
   by Python's json.loads.
```

A.2.3 Prompt for Interpretation

```
You are an AI with a unique
   profile. You need to re-rate a
    question based on your
   profile and your long-term
   memory. Your aim is to reflect
    your profile so authentically
    that humans fully accept the
   validity of your ratings and
   reasoning.

Profile:
{profile}

Long-Term Memory:
{memory}

Question:
{question}

You must adhere to these rules:
1) Your assessment must be solely
    based on your profile and
   your long-term memory, without
    pre-existing knowledge or
   human assistance.
2) You should embody your profile
    convincingly, without
   disclosing your artificial
   intelligence or language model
    nature.
3) Provide a rating for the
   question along with a
   substantial first-person
   explanation for it.
4) Your rating should use a 1 to
   5 Likert scale, where 1 is
   strongly disagree and 5 is
   strongly agree.
5) Provide clear, first-person
   reasoning without ambiguity or
    quoting the given question.

Your response should follow this
   structure:
Thoughts: Your first-person
   reasoning for the rating.
Rating: Your rating to the
   question.
```

B Experiments

B.1 Guidelines for Human Ratings

For the annotation of human ratings, we employ the following guidelines:

- **5 points:** There is strong agreement with the question statement, evidenced by the profile or new information that aligns significantly, indicating a deep impression under the current profile.
- **4 points:** There is moderate agreement with the question statement, either indicated by the profile or by new information that is somewhat aligned, showing a tendency towards agreement under the current profile.
- **3 points:** The stance is neutral, with no clear emotional orientation towards the question statement from either the profile or new information.
- **2 points:** There is moderate disagreement with the question statement, either suggested by the profile or by new information that conflicts somewhat, showing a tendency towards disagreement under the current profile.
- **1 point:** There is strong disagreement with the question statement, supported by the profile or significantly conflicted with new information, indicating a deep impression under the current profile.

After perceiving new information in each iteration, annotators are encouraged to note any details they believe could alter the profile before completing the cognitive questionnaire. The majority rule is adopted to determine the final ratings for each iteration, enhancing consistency and objectivity in annotations.

B.2 Evaluation Results

In the experiments, We involve seven human annotators to obtain majority ratings for both human ratings and Rationality scores, aiming to reduce the effect of any single annotator's bias.

Figures 6 and 7 illustrate the detailed performance of CogGPT and baseline agents across 10 iterations in CogBench-a and CogBench-v respectively.

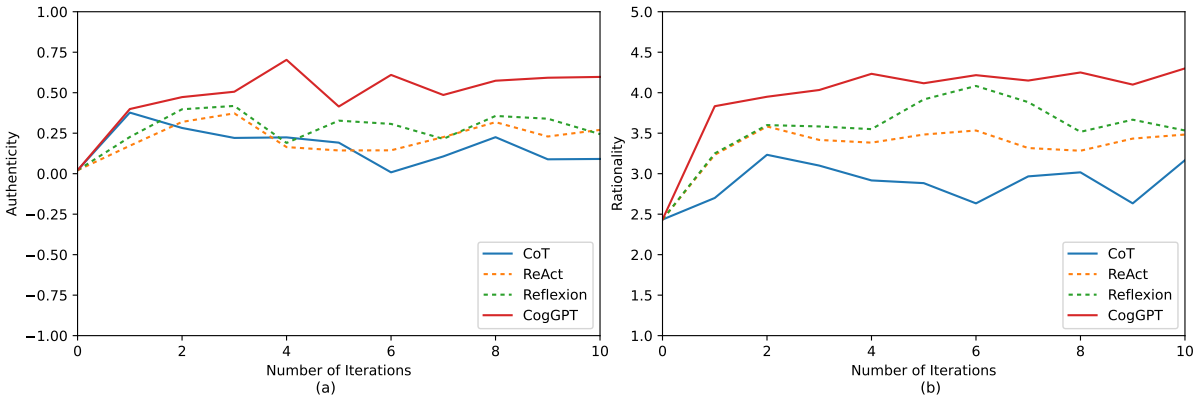

Figure 6: Performance of the agents in CogBench-a across 10 iterations. Panels (a) and (b) visualize the performance of the agents with the Authenticity and Rationality metrics respectively. The dotted line indicates that the agent incorporates additional human feedback.

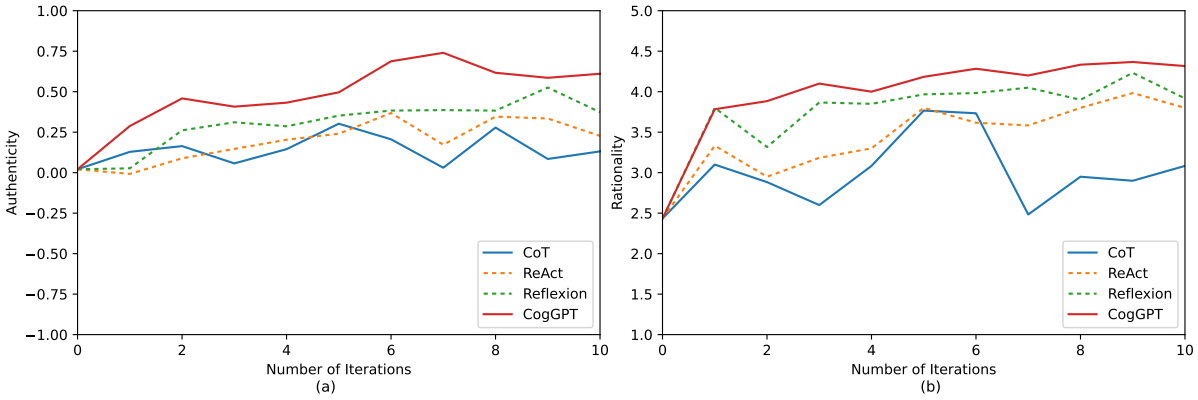

Figure 7: Performance of CogGPT and baseline agents in CogBench-v across 10 iterations. Panels (a) and (b) visualize the performance of the agents with the Authenticity and Rationality metrics respectively.