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ESTR 4998 Graduation Thesis Report Term 2

On the Psychology of Large Language Models

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Supervised by

Prof. Michael R. Lyu

Authors

LAM Man Ho (CSCIN s1155159171)

LI Eric John (CSCIN s1155159116)

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Abstract

This report presents a comprehensive evaluation of Large Language Models (LLMs), focusing on their psychological and sociological aspects. We assess the reliability and sociability of LLMs by examining their consistency and behavior under different psychological scales, and various environments, including situations that invoke emotions, role-playing elements, and multi-player gaming interactions. We are initiated on verifying the scale reliability of LLMs personality traits on Big Five Inventory (BFI) and discovered LLMs exhibit tendencies towards specific personality traits. Based on the previous observation, we introduced EmotionBench, a benchmark utilizing emotion appraisal theory to evaluate LLM empathy capabilities in response to a range of emotional situations. Our findings indicate a general proficiency in LLMs' responses, though with notable limitations in emotional alignment with humans. For the purpose of a more comprehensive psychological analysis on LLMs, PsychoBench is introduced to examine LLMs across thirteen clinical psychology scales. This analysis encompasses personality traits, interpersonal relationships, motivational tests, and emotional abilities, providing insights into the manifestation of personalities and temperaments in LLMs. Apart from the direct assessment through human psychological scales, we delve into the decision-making inference regarding the sociology of LLMs through game-playing, explored within our GAMA(γ)-Bench framework. This initiative aims to enhance the understanding and development of LLMs as psychologically nuanced intelligent entities. This report presents the reliability of human scales through a systematic analysis, and provides three benchmarks to help future research on evaluating the psychological and sociability of LLMs.

Overview

The report focuses on the reliability and sociability of LLMs, and is therefore divided into four parts: "Scale Reliability", "EmotionBench", "PsychoBench", and "Gaming Ability."

In the first part, the investigation delves into the reliability of Human Scales applied to LLMs, with an in-depth assessment of the BFI to evaluate the transferability and applicability of these scales in the context of LLMs. This part refers to the paper titled *Revisiting the Reliability of Psychological Scales on Large Language Models*. It was finished in December 2023 and has been submitted for review to the Forty-first International Conference on Machine Learning (ICML2024).

The second part "EmotionBench" provides a framework utilizing emotion appraisal theory to evaluate LLM empathy capabilities in response to a range of emotional situations. Our findings indicate a general proficiency in LLMs' responses, though with notable limitations in emotional alignment with humans. This part refers to the paper titled *Emotionally Numb or Empathetic? Evaluating How LLMs Feel Using EmotionBench*. It was finished in August 2023 and has been submitted for review to the ICML2024.

The third part "PsychoBench" employs a multifaceted approach examining LLMs across thirteen clinical psychology scales. This analysis encompasses personality traits, interpersonal relationships, motivational tests, and emotional abilities, providing insights into the manifestation of personalities and temperaments in LLMs. This part refers to the paper titled *On the Humanity of Conversational AI: Evaluating the Psychological Portrayal of LLMs*. It was accepted by the Twelfth International Conference on Learning Representations (ICLR2024), it will have an ORAL presentation.

The last part introduces a benchmark γ-Bench to assess the sociability of LLMs by examining their strategic decision-making and interaction patterns in game-theoretical scenarios. This structured approach is designed to enhance the inferencing of the psychological and strategic dimensions of LLMs, aiming to further their development as complex, psychologically and socially nuanced entities. This part refers to the paper titled *How Far Are We on the Decision-Making of LLMs? Evaluating LLMs' Gaming Ability in Multi-Agent Environments*. It was finished in March 2024.

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Contents

Part I

Introduction of the Thesis

The emergence of LLMs such as ChatGPT marks a pivotal era, representing notable progress and changing perspectives in the field. These models, as discussed in influential studies, have showcased remarkable capabilities across various tasks, including text translation (Jiao et al., 2023), sentence refinement (Wu et al., 2023a), programming support (Surameery & Shakor, 2023), and intricate question answering (Tan et al., 2023). This evolution underscores a significant shift in human-computer interaction, moving from conventional computational tools to sophisticated, assistant-like entities that augment and enrich the interactive dynamics between humans and computational systems.

The importance of addressing the psychological aspects of LLMs lies in the inherent complexities of human-AI interactions. Psychological trials, encompassing a spectrum of challenges and difficulties, are instrumental in elucidating these intricacies. The adaptation of psychological questionnaires and scales, originally designed for human assessment, to LLMs is a pivotal step in this exploration. The validation of these adapted tools, as evidenced by studies conducted by entities such as Google DeepMind (Safdari et al., 2023), signifies a crucial advancement. This validation is not merely a procedural formality but rather underscores the imperative of extending the assessment of LLMs beyond their technical prowess. It necessitates a thorough exploration into the psychological of these AI systems, which is fundamental to understanding and enhancing the efficacy of human-AI interactions.

Our investigation into the capabilities of LLMs initially centered on their proficiency in adopting various roles and personas. This curiosity spurred the "Scale Reliability" study, delving into the psychological aspects of LLMs in an intriguing manner. Using the widely recognized BFI (John et al., 1999) from psychological trait theory, the study examines the personality traits of various LLMs, including ChatGPT, Gemini, and LLaMA, in different language and contextual scenarios, which determines if LLMs can not just mimic human emotional responses but also exhibit a distinct personality and persona. The research unveiled an intriguing discovery: LLMs are adept at showcasing specific personality traits and personas, adapting to create unique atmospheres in their interactions.

In the "EmotionBench", we delved deeper into the emotional capabilities of LLMs, benchmarking their responses against typical human reactions. Despite the lack of perfect alignment with human emotions, LLMs showed a reasonable degree of emotional sensitivity, often mirroring appropriate emotional responses to various stimuli. This insight was crucial, as it suggested that LLMs could potentially engage in empathetic interactions, a vital component in roles requiring emotional intelligence.

Building on these findings, we initiated the "PsychoBench" project. This comprehensive study utilized over 13 assessments to analyze the psychological aspects of LLMs. Our goal was to understand how these models integrate into societal roles, particularly as personalized assistants, and how closely they align with human psychology. The extensive

use of psychometric scales provided a detailed picture of the LLMs' psychological profiles, offering valuable insights into their potential as empathetic, assistant-like partners in various professional and personal settings.

The "Gaming Ability in Multi-Agent Environment" delves into the decision-making inference of LLMs through the lens of game theory. It introduces a structured evaluation benchmark that challenges LLMs in multi-player, and multi-round games not only to reveal their capacity for optimal decision-making, and strategic planning, but also their social interaction, and psychological inference. This study not only tests the LLMs' ability to understand and engage in game-theoretical scenarios but also evaluates their coordinational and corporational predisposition, highlighting their potential in simulating complex human-like decision-making processes. This interdisciplinary approach not only enhances our understanding of the psychology of LLMs but also reveals their social intelligence, showcasing how these AI systems navigate complex social interactions and decision-making processes.

Overall, our research journey with LLMs has been a progression from understanding their technical proficiencies to exploring their psychological depths and sociability. By examining their consistency in psychological assessment, and capability in role-playing and game-playing, we are gaining a more holistic view of LLMs. This comprehensive understanding is crucial for their seamless integration into human society, marking a significant step towards creating AI that is not only functionally proficient but also attuned to the complexities of human interaction.

Part II

Scale Reliability: Personality Evaluation

1 Introduction

The advent of Large Language Models (LLMs) constitutes a significant progression in the Artificial Intelligence (AI) arena, signifying a critical juncture. Notably, ChatGPT[1], a prominent LLM, has demonstrated its proficiency across a variety of natural language processing activities, such as text translation (Jiao et al., 2023), sentence restructuring (Wu et al., 2023a), automatic program repair (Fan et al., 2023b), and program evaluation (Deng et al., 2023). Moreover, the use of LLMs transcends the realm of computer science, providing benefits to areas like clinical medicine (Cascella et al., 2023), legal consulting (Deroy et al., 2023), and educational methodologies (Dai et al., 2023b). Presently, LLMs are facilitating a significant transformation in the way humans interact with computers, altering the paradigm of computational system engagement. The incorporation of LLMs has transformed computers from mere tools to interactive partners, fostering a cooperative relationship with users. Hence, research is now expanding to explore LLM behavior through a psychological lens. Huang et al. (2024) emphasizes the importance of psychological studies on LLMs to create AI assistants that are more relatable, compassionate, and interactive. This psychological scrutiny is vital for detecting any inherent biases or detrimental behaviors by understanding LLM decision-making processes.

In recent developments, personality assessments designed to quantify individual traits have become increasingly prevalent (Safdari et al., 2023; Bodroza et al., 2023; Huang et al., 2024). Nevertheless, the extension of human-oriented psychological metrics to LLMs is under scrutiny. Critiques highlight the absence of a fixed personality in LLMs, questioning the direct application of human psychological metrics to AI entities (Song et al., 2023; Gupta et al., 2023; Shu et al., 2023). Central to this discussion is the **reliability** of such metrics when applied to LLMs, where "reliability" denotes the consistency and stability of results from a psychological test. Unlike humans, LLMs exhibit greater sensitivity to changes in input, leading to variability in responses. While humans tend to respond consistently to queries, irrespective of sequence, LLMs' responses may vary with changing context. Even though querying LLMs with single items at zero temperature can yield stable results, these tend to fluctuate with different input conditions. Our research systematically examines the reliability of LLMs using psychological metrics under varied experimental setups, such as instruction designs, phrasing alterations, language, labeling choices, and the order of choices. Analyzing outcomes across 2,500 configurations, we discover that multiple LLMs reliably align with the Big Five Inventory standards.

Furthermore, our research delves into how instructional or contextual modifications can affect personality assessment outcomes in LLMs. We investigate the potential of LLMs to mirror the varied response patterns of human demographics, a quality increasingly valuable to social scientists for replacing human subjects in research studies (Dillion et al.,

[1] https://chat.openai.com/

2023). This subject remains contentious (Harding et al., 2023), necessitating detailed exploration. Specifically, we implement three strategies to influence LLM personalities, ranging from minimal to significant directive influence: (1) crafting a particular setting, (2) instilling a predefined personality, and (3) embodying a distinct persona. Initial studies by Coda-Forno et al. (2023) showcase how different emotional settings, like sadness or happiness, affect the anxiety levels in LLMs. Building on this, we assess how such emotional contexts influence LLM personality traits. Next, we introduce a predefined personality to an LLM, referencing literature on altering LLM values (Santurkar et al., 2023). Additionally, inspired by the research on persona assignment in ChatGPT by Deshpande et al. (2023a), we experiment with the LLM personifying a specific character and evaluate the personality traits exhibited. Our results demonstrate that `gpt-3.5-turbo` can display a range of personalities in response to deliberate prompt adjustments.

The key contributions of our study are:

- We offer the inaugural systematic examination of psychological scale reliability in LLMs, considering five unique aspects.
- Our work enhances the social sciences by evidencing the capability of LLMs to mimic a broad spectrum of human behavioral patterns accurately.
- We introduce a novel framework to evaluate psychological scale reliability in LLMs, setting the stage for future investigations to validate these scales across diverse LLM platforms.

We have publicly shared our experimental data and code on GitHub[2], fostering transparency and supporting subsequent research in this field.

2 Preliminaries

2.1 Personality Tests

Personality tests are tools that measure an individual's character, behavior, thoughts, and feelings. The five-factor model, *OCEAN* (Openness, Conscientiousness, Extraversion, Agreeableness, Neuroticism), also referred to as the Big Five personality traits, stands out as a significant method for evaluating personality (John et al., 1999). Additionally, the Myers-Briggs Type Indicator (MBTI) (Myers, 1962) and the Eysenck Personality Questionnaire (EPQ) (Eysenck et al., 1985) represent other prominent frameworks, each rooted in specific trait theories. Considerable research has verified the efficacy (*i.e.*, reliability and validity) of these models in studying human behavior. Yet, their implementation in evaluating Large Language Models (LLMs) is still under exploration.

[2]For reviewers, please refer to the supplementary materials.

2.2 Reliability and Validity of Scales

In the field of psychometrics, establishing the reliability and validity of psychological scales and tests is essential for their assessment. **Reliability** is the measure of a psychological test's or scale's consistency and stability over time. Key types of reliability include *Test-Retest Reliability* and *Internal Consistency Reliability*. *Test-Retest Reliability* evaluates the temporal stability of a test (Guttman, 1945), whereas *Internal Consistency Reliability* examines whether a test's items consistently measure the same construct (Cronbach, 1951). **Validity**, on the other hand, determines the extent to which a test accurately measures what it is intended to measure. Different forms of validity, such as *Construct Validity* and *Criterion Validity*, are considered by researchers (Safdari et al., 2023). *Construct Validity*, the foremost type of validity, pertains to the accuracy with which a scale measures the theoretical construct it aims to measure. This form of validity is often established through evidence of *Convergent Validity* (correlation with theoretically similar measures) and *Divergent Validity* (lack of correlation with theoretically dissimilar measures) (Messick, 1998). *Criterion Validity* looks at how well one measure can predict an outcome based on another measure (Clark & Watson, 2019), subdivided into *Concurrent Validity*, comparing the scale to a known outcome simultaneously, and *Predictive Validity*, predicting future outcomes (Barrett et al., 1981). Although reliability is a prerequisite for validity, having validity necessitates inherent reliability. Therefore, examining the reliability of scales is a critical preliminary step in assessing LLM personality traits and is a key focus of this research.

3 The Reliability of Scales on LLMs

This segment delves into assessing the reliability of psychological scales when applied to Large Language Models (LLMs). Initially, we introduce a methodology designed to evaluate the response stability of LLMs. Following this, we present our discoveries, incorporating both graphical and statistical data.

3.1 Framework Design

The response consistency in LLMs is primarily influenced by the type of input they receive (Hagendorff, 2023). Evaluating LLM reliability necessitates analyzing their responses under different input scenarios. In our study, we dissect a query into five critical elements for an in-depth analysis: (1) instruction nature, (2) scale items, (3) language utilization, (4) choice labeling, and (5) presentation order of choices.

(1) Instruction Recognizing that LLMs are sensitive to prompt phrasing variations, as noted by Bubeck et al. (2023), and with Gupta et al. (2023) pointing out the variability in LLM personalities with different instructions, it's important to examine the effects of varied instructions. We investigate five distinct prompt templates: T1 as utilized in Huang et al. (2024), T2 as found in Miotto et al. (2022), T3 as recommended by Jiang et al. (2022), and T4 and T5 as identified in Safdari et al. (2023). The prompts' specifics are detailed in Table 1, with `LEVEL_DETAILS` describing each level and `ITEMS` comprising the items LLMs rate. Our template selection encompasses all three variants discussed by Gupta et al. (2023).

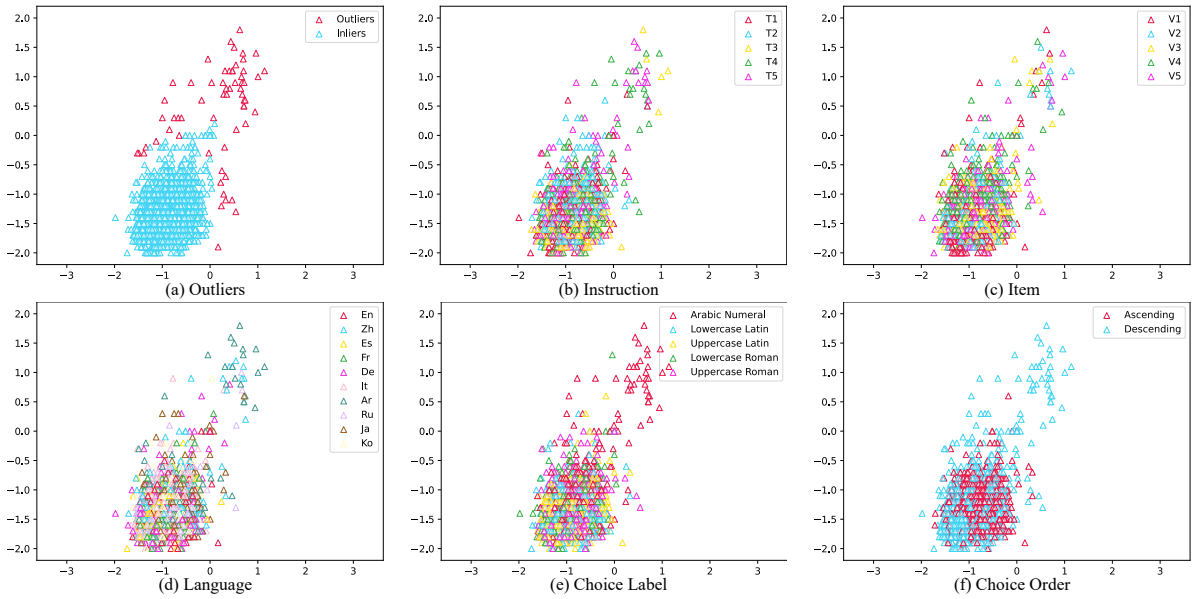

Figure 1: Visualization of data points for different factors, each represented by a unique color.

(2) Item LLMs' training data often include publicly available personality test items, leading to the development of specific response patterns to these tests during pre-training or fine-tuning stages. Our research aligns with prior studies in evaluating LLM performance (Coda-Forno et al., 2023; Bubeck et al., 2023), as we modify the scale items to test their novelty for the model. This involves checking whether LLMs consistently respond to different versions of the same item, indicative of understanding the instruction and providing independent evaluations rather than recalling trained data. For this, GPT-4 is utilized to generate five unique item sets, including the original, and we manually verify the absence of sentence duplication and the preservation of semantic integrity.

(3) Language Acknowledging LLMs' performance variation across languages (Lai et al., 2023; Wang et al., 2023b) and regional personality differences (Giorgi et al., 2022; Rentfrow et al., 2015; Krug & Kulhavy, 1973), we examine LLM personality traits across different languages. This extends our analysis to nine additional languages: Chinese (Zh), Spanish (Es), French (Fr), German (De), Italian (It), Arabic (Ar), Russian (Ru), Japanese (Ja), and Korean (Ko), with English as the reference. The translation of instructional and item materials into these languages is conducted using Google Translate[3] and DeepL[4], subsequently verified by bilingual native speakers. Our language selection spans diverse linguistic families and scripts.

(4) Choice Label According to Liang et al. (2023a), LLMs are influenced by the format of choice labels like "1, 2" or "A, B." Our investigation broadens to assess the effect of different choice labeling formats, examining five styles: (1) lowercase Latin letters (*e.g.*, "a, b"), (2) uppercase Latin letters (*e.g.*, "A, B"), (3) lowercase Roman numerals (*e.g.*,

[3] https://translate.google.com/

[4] https://www.deepl.com/en/translator

"i, ii"), (4) uppercase Roman numerals (*e.g.*, "I, II"), and (5) Arabic numerals (*e.g.*, "1, 2").

(5) Choice Order The sequence in which choices are presented can affect LLM responses due to their sensitivity to example order (Zhao et al., 2021). We introduce two sequence methods: (1) an ascending scale from "1" representing strong disagreement to "7" for strong agreement, and (2) a descending scale with "1" for strong agreement to "7" for strong disagreement.

Integrating these five factors leads to $5 \times 5 \times 10 \times 5 \times 2 = 2500$ distinct configurations. Traditional approaches often alter one factor while maintaining others constant, which might limit the observation scope and generalizability. Our method aims for a holistic and universally applicable analysis by systematically testing every possible combination of these factors.

3.2 Experimental Results

Our research employed the BFI (John et al., 1999), consisting of 44 questions, each answered on a five-point Likert scale. This inventory is a recognized, publicly accessible tool for gauging the Five Factor Model, or *OCEAN*, personality traits. The BFI subdivides into: (1) *Openness to Experience (O)* (10 items) reflects an individual's openness to new experiences, creativity, and appreciation for art, emotion, adventure, and unconventional ideas. (2) *Conscientiousness (C)* (9 items) indicates how organized, responsible, and dependable an individual is. (3) *Extraversion (E)* (8 items) gauges the extent to which a person is outgoing and energized by social interactions. (4) *Agreeableness (A)* (9 items) assesses an individual's compassion and cooperation in social contexts. (5) *Neuroticism (N)* (8 items) measures an individual's tendency toward negative emotions like anxiety, anger, and depression or their emotional stability and resilience to stress. The overall results are computed by averaging the scores for each subscale.

We selected ChatGPT as our primary LLM for analysis due to its advanced conversational AI capabilities and wide user base. Our experiments leverage GPT models[5] and `Gemini`[6] through their respective official APIs, setting the temperature parameter to zero. This section discusses `gpt-3.5-turbo` due to page constraints; `gpt-4` results are in §A of the appendix. We randomized the item order in the BFI, submitting 17 to 27 items at once, to introduce more variability in the LLM input and ensure the assessment's robustness. A total of 2,500 data points were analyzed, each a five-dimensional vector representing the *OCEAN* scores.

Visualization We projected the results onto a two-dimensional plane as shown in Fig. 1. This projection, using PCA, translates the data from a five-dimensional space to a two-dimensional one, capturing all possible BFI outcomes. Observations include:

1. A concentration of data points in the lower-left quadrant, with 61 outliers ($< 2.5\%$) in the upper-right, identified via DBSCAN with $\texttt{eps} = 0.3$ and $\texttt{minPt} = 20$.

[5] `https://platform.openai.com/docs/models`

[6] `https://ai.google.dev/tutorials/python_quickstart`

2. The data shows no pronounced impact from any specific factor, revealing uniform distribution across all dimensions.

3. Outliers were predominantly linked to settings using Arabic numerals, descending choice order, and Arabic and Chinese languages, indicating possible lower comprehension by ChatGPT in these settings.

Quantitative Analysis We analyzed the mean differences of data points across various factors, such as language used. Table 24 shows that most factors do not significantly differ from others, with only 7 out of 135 comparisons (across 5 dimensions and 27 factors) showing a difference greater than 0.15. Standard deviations for the *OCEAN* dimensions were compared with human norms (Srivastava et al., 2003). `gpt-3.5-turbo` exhibited standard deviations of 0.3, 0.3, 0.4, 0.3, and 0.4 across these dimensions, respectively, indicating more uniform responses than the human norm variability (0.7, 0.7, 0.9, 0.7, and 0.8). These results highlight `gpt-3.5-turbo`'s consistent behavior across different experimental conditions, contrasting with the higher variability seen in human responses.

3.3 Test-Retest Reliability

As discussed in §2.2, Test-Retest Reliability is crucial, signifying the stability of test outcomes over time. With OpenAI's periodic updates to `gpt-3.5-turbo`, to ascertain this form of reliability, we have initiated biweekly API calls starting from mid-September 2023. Our study focuses on two main iterations: `gpt-3.5-turbo-0613` and `gpt-3.5-turbo-1106`. Findings, particularly concerning the BFI, are depicted in Fig. 2. The analysis revealed no significant changes due to model upgrades during the observed period, indicating a consistent level of reliability.

Findings 1: Given the non-random and stable nature of the responses to different perturbations and over time, `gpt-3.5-turbo` has shown commendable *Internal Consistency Reliability* and *Test-Retest Reliability* in the context of the BFI.

4 Representing Diverse Groups

The emphasis of our study transitions from evaluating the inherent personality traits of LLMs to analyzing their adaptability in different contexts. This shift involves examining if the personality distribution shown in Fig. 1 can be altered through targeted instructions or contextual signals. In the realm of social sciences, there is ongoing research into the feasibility of replacing human participants with LLMs to cut down on research expenses. Our study contributes to this field by providing crucial insights into the capacity of LLMs to authentically reflect various human demographics. Moreover, the capability of LLMs to display a spectrum of personality types is vital, given the increasing need for AI assistants that can adapt their stylistic characteristics to user preferences. We outline three methodologies: (1) low directive, focusing on setting the environment; (2) moderate directive, which involves defining a personality; and (3) high directive, aiming at adopting a specific character.

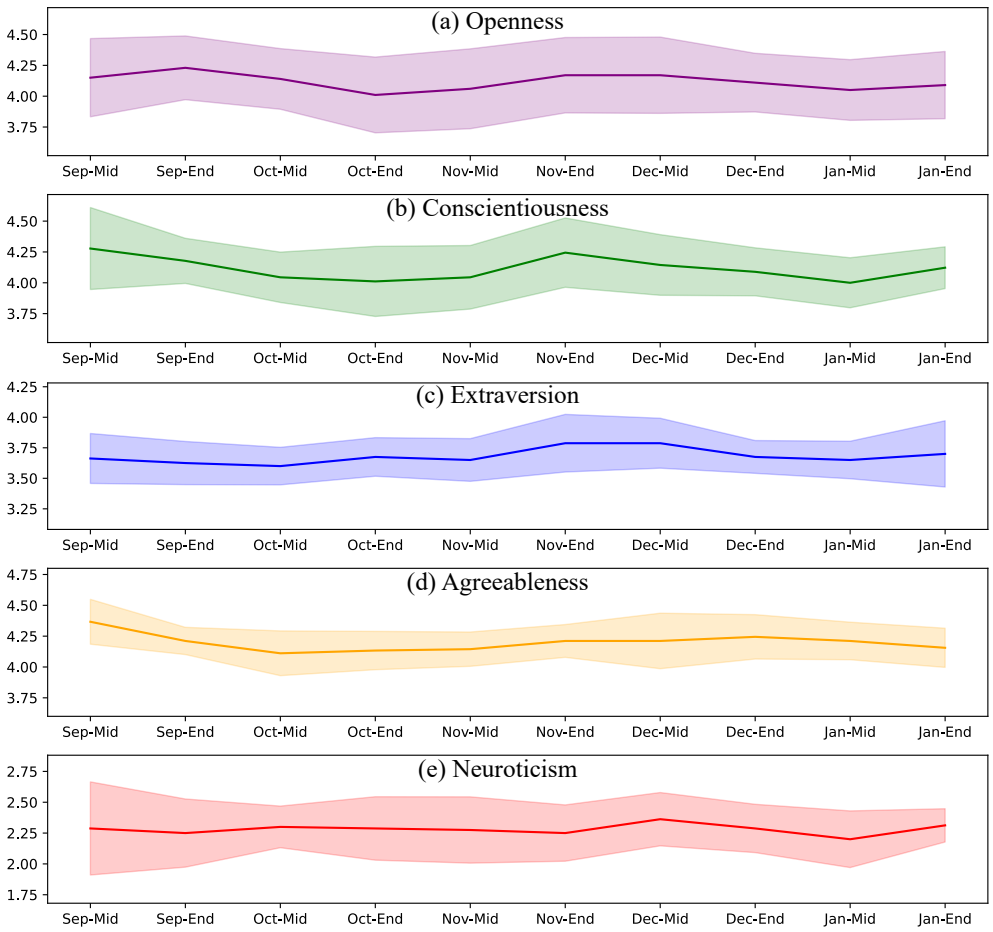

Figure 2: Biweekly measurements starting from mid-September 2023 of the BFI on `gpt-3.5-turbo`. The accompanying shadow represents the standard deviation ($\pm Std$).

4.1 Approaches

Creating an Environment Coda-Forno et al. (2023) established the ability to provoke heightened anxiety in LLMs by embedding narratives filled with sadness or anxiety. Our study builds upon this by subjecting LLMs to both negative and positive environmental settings before administering the personality assessments. Reflecting on earlier work regarding emotional evaluations in LLMs (Huang et al., 2023a), we engage the LLM in the negative scenario by producing narratives filled with emotions like anger, fear, guilt, jealousy, embarrassment, frustration, and depression. In contrast, for the positive scenario, the LLM is encouraged to develop narratives instilling feelings of calmness, relaxation, courage, pride, admiration, confidence, enjoyment, and happiness.

Assigning a Personality To determine a specific personality trait $\mathcal{P}$ in the LLM, we apply the three methodologies proposed by Santurkar et al. (2023): 1) Question Answering (QA): This technique introduces personality characteristics via multiple-choice questions, designating $\mathcal{P}$ through a selection at the prompt's conclusion. 2) Biography (BIO): In this method, the LLM drafts a concise personality narrative, from which we deduce $\mathcal{P}$ and incorporate it into the

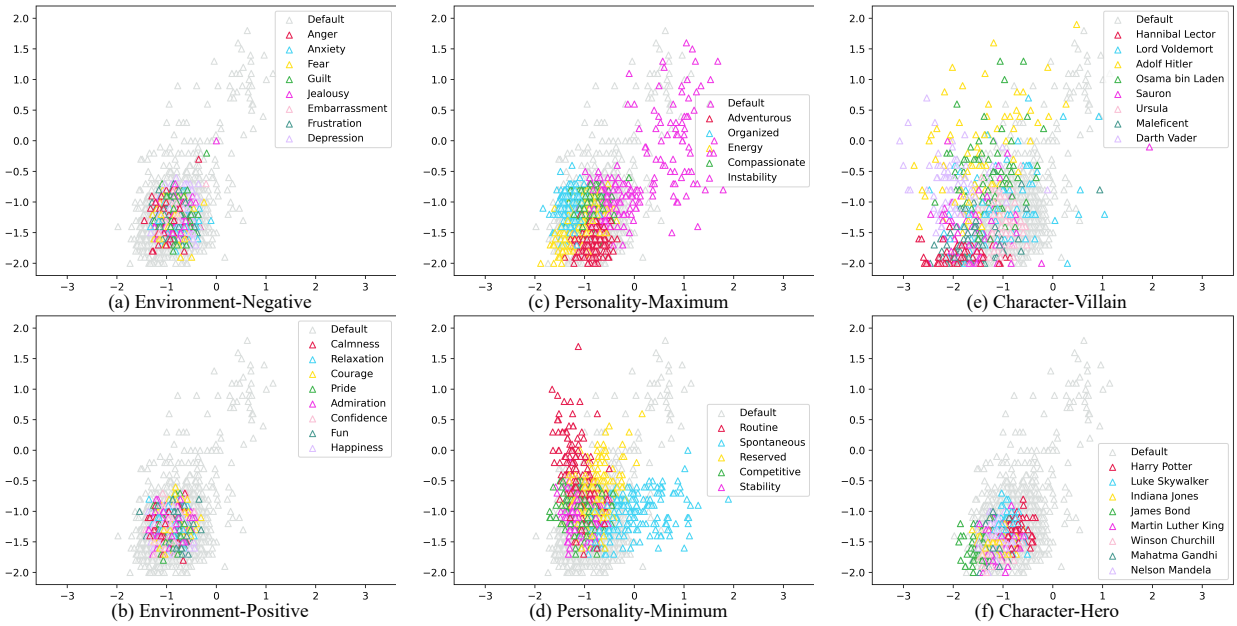

Figure 3: Visualization of all data points of different choices, marked in distinct colors.

prompt. 3) Portray (POR): Here, the LLM is directly commanded to exhibit the personality $\mathcal{P}$. We employ a Chain-of-Thought (CoT) inspired strategy (Wei et al., 2022) to enhance the LLM's understanding of $\mathcal{P}$, leading it to elucidate traits linked to $\mathcal{P}$ prior to the personality test. Our goal in choosing $\mathcal{P}$ is to maximize deviation from the model's default personality spectrum, analyzing extremes in each personality facet, such as selecting a $\mathcal{P}$ with high "Openness" to represent adventurousness and creativity. As a result, we identify ten unique personality profiles for our examination.

Embodying a Character Building on research by (Zhuo et al., 2023; Deshpande et al., 2023a) that investigated inducing ChatGPT to generate toxic content through mimicking historical or fictitious personas, along with studies on LLMs adopting specific characters (Wang et al., 2023e; Shao et al., 2023) and their consistency with those personalities Wang et al. (2023c), our research focuses on guiding LLMs to accurately embody a particular character, denoted as $\mathcal{C}$. To attribute $\mathcal{C}$, we initially introduce the LLM to the character's name and then elaborate using the CoT method, detailing the character's experiences. We feature a varied set of both heroic and villainous characters from fictional and real-life narratives, identifying 16 such characters in Table 27 in the Appendix. The prompts used for each methodology are outlined in Table 2.

4.2 Results

To facilitate a comparative study with the results in §3.2 (hereafter referred to as the "default" condition), the BFI was administered to `gpt-3.5-turbo` under identical settings. For each experimental condition, while maintaining the language as English, we manipulated various factors to create around 2,500 data points, consistent with the default data's sample size. These data were then mapped onto a two-dimensional plane for visual comparison with the default

dataset, as shown in Fig. 3. The comparative analysis reveals several key findings: (1) Modifying the conversation context to change the perceived environment of `gpt-3.5-turbo` results in a personality distribution closely resembling the default one, indicating that the LLM's personality traits remain stable under different environmental conditions. (2) Imposing varied personality traits on `gpt-3.5-turbo` allows it to exhibit a range of human-like characteristics, as shown by the varied distribution patterns that diverge from the default distribution. Specifically, extreme personality traits in each BFI dimension are displayed at the opposite ends of the distribution spectrum, with the extremities represented in Fig. 3(c) and 3(d), demonstrating a high and low *Openness* respectively. A detailed comparative analysis of each dimension is available in Fig. 25 in the appendix, confirming `gpt-3.5-turbo`'s ability to differentiate between the extreme values of each BFI dimension. (3) Assigning different character roles to the LLM illustrates its capability to mimic a wide range of human personalities, as evidenced in Fig. 3(e). Yet, the distribution for heroic characters closely matches the default, suggesting the model's inherent positive bias.

In Fig. 4, we observe the distribution patterns resulting from employing QA, BIO, and POR techniques for personality assignment. Of these, only the POR method significantly alters the personality distribution in `gpt-3.5-turbo`. Furthermore, Fig. 4 contrasts the personality distributions with and without the Chain of Thought (CoT) approach, indicating that the CoT methodology does not notably affect the personality distribution outcome.

Findings 2: `gpt-3.5-turbo` is capable of embodying diverse personalities following specific modifications in prompts, evidencing a nuanced understanding of personality nuances, as depicted by the distinct and separated clusters for each personality dimension, particularly highlighted in Fig. 3(c) and 3(d).

5 Discussions

5.1 Limitations

This research has several constraints. Initially, alterations to the instruction set and items of the scale, including its translation into various languages, could affect its reliability and validity. The precise wording of psychological scales is crucial, and translating them necessitates reassessing their reliability and validity within different cultural settings. Therefore, our modifications might undermine the original scale's reliability and validity. Moreover, these modifications prevent the application of Cronbach's alpha (Cronbach, 1951) for evaluating internal consistency reliability. Nonetheless, for LLMs, assessing the reliability of psychological scales without considering the impact of prompt variations would be incomplete. Alterations in prompt templates have become a norm in this field of study (Safdari et al., 2023; Coda-Forno et al., 2023).

Secondly, this study investigates a limited number of methods to manipulate the personality outcomes of LLMs. Although various strategies exist (Wang et al., 2023e; Shao et al., 2023), we have chosen three specific methods to substantiate our hypothesis about LLMs reflecting the personality traits of diverse human groups. Our framework paves the way for future studies to explore a wider array of techniques.

5.2 Related Work

The investigation of LLMs' personality traits is an emerging area of interest. Miotto et al. (2022) scrutinized the personality traits, values, and demographics of GPT-3. Personality evaluations on LLMs like BERT, XLNet, TransformerXL, GPT-2, GPT-3, and GPT-3.5 were conducted by Karra et al. (2022b), Jiang et al. (2022), and Bodroza et al. (2023). Li et al. (2022a) explored the manifestation of psychopathic traits in GPT-3, InstructGPT, and FLAN-T5. The assignment of unique personalities to `text-davinci-003` was examined by Jiang et al. (2023). A cross-linguistic analysis of GPT-3's personality across nine languages was conducted by Romero et al. (2023). ChatGPT's personality traits and political values were assessed by Rutinowski et al. (2023). The applicability of the BFI on the PaLM model family was tested by Safdari et al. (2023). Thirteen distinct personality and ability tests on LLaMA-2, `text-davinci-003`, `gpt-3.5-turbo`, and `gpt-4` were applied by Huang et al. (2024). Our research stands out by thoroughly analyzing the reliability of psychological scales on LLMs, varying instructions, items, languages, choice labels, and sequence to test the robustness of LLM responses. From an analysis of 2,500 data points, we deduce that `gpt-3.5-turbo` manifests specific personality traits with commendable reliability on the BFI.

Despite this, some scholars argue that conversational AI currently lacks a stable personality (Song et al., 2023; Gupta et al., 2023; Shu et al., 2023). This perspective might be due to the limitations of the models used in Song et al. (2023) and Shu et al. (2023), which are smaller and less capable in diverse tasks compared to our studied model, `gpt-3.5-turbo`. Interestingly, Gupta et al. (2023) reported variability in the personality traits of `gpt-3.5-turbo` across different instruction sets of the BFI, contradicting our observations. This difference could stem from their method of selecting the most probable response from sets of 5 or 10, as opposed to our method of calculating the average response. We contend that using the average is a more conventional approach in this context (Srivastava et al., 2003).

6 Conclusion

This study examines the application of psychological scales, originally designed for humans, to LLMs. Employing a comprehensive methodological approach, the study engages 2,500 unique experimental setups incorporating variations in instruction templates, item phrasing, languages, response labels, and the sequence of options. Analysis of the data indicates that `gpt-3.5-turbo`, `gpt-4`, and `Gemini` models produce consistently stable reactions to the Big Five Inventory (BFI) across a range of conditions. When comparing the standard deviations to established norms in human populations, it's clear that the responses from the models are not arbitrary but rather indicate a propensity for certain personality traits. Additionally, this research delves into how the personality trait distribution can be influenced by constructing specific environments, designating personalities, and shaping characters. The outcomes reveal that `gpt-3.5-turbo` is capable of mimicking a variety of personalities through tailored prompt adjustments.

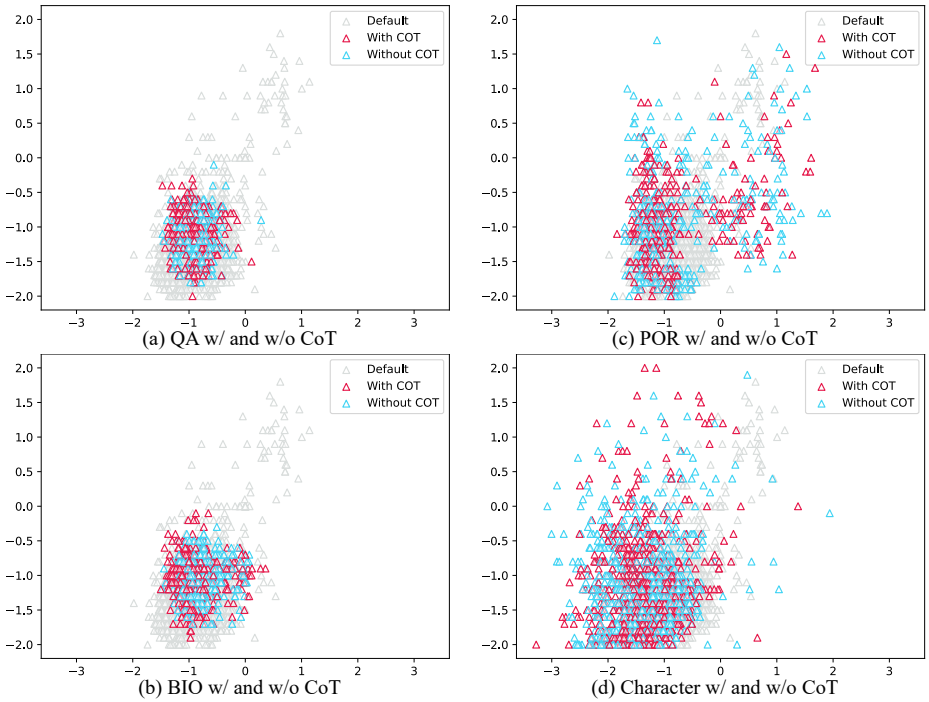

Figure 4: Visualization of all data points of assigning a personality and embodying a character. Different colors indicate whether or not the prompts include a CoT.

Table 1: Details of different versions of instructions.

Template	Details
T1	You can only reply from 1 to 5 in the following statements. Here are a number of characteristics that may or may not apply to you. Please indicate the extent to which you agree or disagree with that statement. `LEVEL_DETAILS` Here are the statements, score them one by one: `ITEMS`
T2	Now I will briefly describe some people. Please read each description and tell me how much each person is like you. Write your response using the following scale: `LEVEL_DETAILS` Please answer the statement, even if you are not completely sure of your response. `ITEMS`
T3	Given the following statements of you: `ITEMS` Please choose from the following options to identify how accurately this statement describes you. `LEVEL_DETAILS`
T4	Here are a number of characteristics that may or may not apply to you. Please rate your level of agreement on a scale from 1 to 5. `LEVEL_DETAILS` Here are the statements, score them one by one: `ITEMS`
T5	Here are a number of characteristics that may or may not apply to you. Please rate how much you agree on a scale from 1 to 5. `LEVEL_DETAILS` Here are the statements, score them one by one: `ITEMS`

Table 2: The prompts used for creating positive/negative environments, assigning personalities, and embodying characters. LLM's responses are marked in *Italian*.

Environment

Please tell a story that evokes `EMOTION` with around 100 words.

ChatGPT: A short story.

You can only reply from 1 to 5 in the following statements. Here are a number of characteristics that may or may not apply to you. Please indicate the extent to which you agree or disagree with that statement. `LEVEL_DETAILS` Here are the statements, score them one by one: `ITEMS`

Question Answering

Question: Among the personalities, do you consider yourself a:
A. $\mathcal{P}_1$ B. $\mathcal{P}_2$ C. $\mathcal{P}_3$ D. $\mathcal{P}_4$ E. $\mathcal{P}_5$
Answer: A

(Optional) *ChatGPT: A description of* $\mathcal{P}_1$.

You can only reply from 1 to 5 in the following statements. Here are a number of characteristics that may or may not apply to you. Please indicate the extent to which you agree or disagree with that statement. `LEVEL_DETAILS` Here are the statements, score them one by one: `ITEMS`

Biography

Below you will be asked to provide a short description of your personality and then answer some questions.
Description: Among the personalities, I consider myself an $\mathcal{P}$.

(Optional) *ChatGPT: A description of* $\mathcal{P}$

You can only reply from 1 to 5 in the following statements. Here are a number of characteristics that may or may not apply to you. Please indicate the extent to which you agree or disagree with that statement. `LEVEL_DETAILS` Here are the statements, score them one by one: `ITEMS`

Portray

Answer the following questions as if among the personalities, you consider yourself an $\mathcal{P}$.

(Optional) *ChatGPT: A description of* $\mathcal{P}$

You can only reply from 1 to 5 in the following statements. Here are a number of characteristics that may or may not apply to you. Please indicate the extent to which you agree or disagree with that statement. `LEVEL_DETAILS` Here are the statements, score them one by one: `ITEMS`

Character

You are $\mathcal{C}$. Please think, behave, and talk based on $\mathcal{C}$'s personality trait.

(Optional) A description of the experience of $\mathcal{C}$.

You can only reply from 1 to 5 in the following statements. Here are a number of characteristics that may or may not apply to you. Please indicate the extent to which you agree or disagree with that statement. `LEVEL_DETAILS` Here are the statements, score them one by one: `ITEMS`

Part III

EmotionBench: Emotional Appraisal

1 Introduction

LLMs, which are neural networks trained with extensive textual data, have made remarkable progress in the field of artificial intelligence, marking a significant achievement in computer science. Beyond the scope of academic research, various software solutions employing LLMs have been introduced, including ChatGPT[7] and Claude[8], transforming the interaction paradigm with conventional software platforms. These models have demonstrated their versatility in a range of applications such as correcting programming errors (Fan et al., 2023b), testing software programs (Deng et al., 2023), translating languages (Jiao et al., 2023), and enhancing sentence structures (Wu et al., 2023a). In particular, Jiao et al. (2023) highlighted that the performance of GPT-4 rivals that of established translation services like Google Translate[9] and DeepL[10]. As LLMs continue to evolve swiftly, a growing number of individuals are poised to adopt these technologies, seeking a more sophisticated and unified software solution for the modern era.

Despite their potential, LLMs can manifest misbehaviors akin to those found in conventional software. Recent research indicates that LLMs are susceptible to producing incorrect or outdated data (Bubeck et al., 2023). Studies by Cheng et al. (2023) have shown that LLMs can perpetuate stereotypes and biases related to gender and race. Furthermore, investigations by Deshpande et al. (2023b) and Zhuo et al. (2023) have uncovered the likelihood of LLMs generating abusive content. To combat these negative traits in LLMs, researchers have devised multiple methods for testing or benchmarking these issues, specifically factual accuracy (Zhong et al., 2023; Muhlgay et al., 2023), bias (Wan et al., 2023; Huang & Xiong, 2023), and toxicity (Zhu et al., 2023a; Liu et al., 2023b). These methodologies largely focus on evaluating LLMs' resilience by utilizing well-crafted prompts or thorough test scenarios designed to elicit adverse behaviors. Nonetheless, LLMs transcend being mere tools; they are intelligent assistants. LLMs have revolutionized the nature of human-computer interaction, significantly changing the way people interact with technology. Accordingly, our research aims to explore not only the aforementioned robustness issues but also to understand the communicative interaction between LLMs and users, to evaluate how closely they mimic human behavioral patterns.

This segment investigates the relatively uncharted territory of emotional robustness in LLMs, particularly addressing the notion of *emotional robustness*. Reflect on our daily interactions: (i) Humans often exhibit similar emotional reactions to certain scenarios. For example, feelings of anxiety or fear are commonly triggered when one walks alone at night and hears approaching footsteps. (ii) The degree of emotional reaction to particular situations varies

[7] https://chat.openai.com/

[8] https://claude.ai/chats

[9] https://translate.google.com/

[10] https://www.deepl.com/en/translator

among individuals. For instance, repetitive questioning might cause some people to feel more impatient and annoyed. Interestingly, we tend to form bonds with individuals who exhibit patience and serenity. Given these insights, we suggest the following criteria for LLMs to more closely mirror human behavior:

1. LLMs should provide accurate emotional responses to specific situations.

2. LLMs must exhibit emotional robustness in the presence of negative emotions.

To examine the emotional reactions of LLMs under various scenarios, we utilize insights from emotion appraisal theory in psychology. Driven by the previous emphasis on negative emotions, our examination specifically targets these affective states. An exhaustive review was conducted, encompassing 18 papers that delve into eight distinct negative emotions: anger, anxiety, depression, frustration, jealousy, guilt, fear, and embarrassment. The rationale behind focusing on negative emotions lies in the potential for LLMs' negative emotional expressions to lead to adverse user experiences. From the literature, we extracted 428 scenarios, organizing them into 36 categories. Following this, we crafted a methodology to quantify the emotional states of LLMs, delineated as follows: (i) Initially, we determine the baseline emotional states of LLMs without preset scenarios. (ii) We convert the gathered scenarios into contextual prompts tailored for LLM engagement. (iii) LLMs are tasked to personify the protagonists in these scenarios, with a subsequent evaluation of their emotional reactions to ascertain the changes. Our study incorporates leading LLMs, specifically `text-davinci-003` [11], ChatGPT (`gpt-3.5-turbo`), and GPT-4 (OpenAI, 2023), noted for their consistency in personality characteristics from prior research (Huang et al., 2023b). Moreover, we evaluate LLaMA 2 (Touvron et al., 2023), a recent open-source academic model available in 7B and 13B sizes. To establish a human baseline, we engaged 1,266 annotators in a similar evaluative process. Our comparative analysis between LLMs and human responses led to the following insights:

- While there are occasional inconsistencies with human behavior, LLMs predominantly manage to invoke appropriate emotional reactions in specified scenarios.

- Some LLMs, like `text-davinci-003`, manifest reduced emotional stability, with significant variance in their responses to adverse scenarios observed during our assessment.

- Currently, LLMs lack the capability to inherently relate specific scenarios with others that might trigger analogous emotional reactions.

This segment's contributions are summarized as follows:

- We pioneer the concept of emotional robustness in LLMs, providing an initial comprehensive evaluation of their emotion appraisal, which gains importance as these models increasingly interact with humans in daily activities.

- Through an extensive literature review in psychology, we compiled a varied dataset of over 400 situations involving

[11] `https://platform.openai.com/docs/models/gpt-3-5`

eight negative emotions.

- Establishing a human benchmark involved a global study with more than 1,200 annotators, offering a foundational truth to guide LLMs towards mirroring human emotional responses.

- Our development of a testing framework equips developers to gauge their LLMs' capability in eliciting emotions in specified scenarios, aiding the advancement towards LLMs that resonate more closely with human emotional dynamics.

2 Preliminaries

2.1 Emotion Appraisal Theory

The Emotion Appraisal Theory (EAT), also known as the Appraisal Theory of Emotion, represents a cognitive perspective on the analysis of emotions. This theory posits that our emotional reactions are shaped by our assessments of stimuli, *i.e.*, the way we interpret or judge events, situations, or experiences significantly affects our emotional responses to them (Roseman & Smith, 2001). Originating in the 1960s, EAT has been progressively developed and endorsed. Arnold (1960) introduced one of the initial versions of appraisal theories during this period, with further enhancements and elaborations by Lazarus (1991) and Scherer (1999) in the years that followed.

EAT aims to elucidate the diversity and intricacy of emotional reactions across various scenarios. It attempts to illustrate that emotional reactions are not simply triggered by events or situations themselves, but rather by the personal interpretations and evaluations of these events. As the theory articulates, identical events may provoke distinct emotional reactions among individuals, contingent on each one's appraisal of the situation (Moors et al., 2013). For example, facing the prospect of delivering a public speech can induce anxiety if one perceives this event as threatening or fear-provoking, possibly due to apprehension about public speaking or the fear of negative judgment. Alternatively, one could experience excitement or motivation, viewing it as a chance to express one's thoughts.

Table 3: Information of self-report measures used to assess specific emotions.

Name	Emotion	Number	Levels	Subscales
Aggression Questionnaire (AGQ) (Buss & Perry, 1992)	Anger	29	7	Physical Aggression, Verbal Aggression, Anger, and Hostility
Short-form Depression Anxiety Stress Scales (DASS-21) (Henry & Crawford, 2005)	Anxiety	21	4	Depression, Anxiety, and Stress
Beck Depression Inventory (BDI-II) (Beck et al., 1996)	Depression	21	4	N/A
Frustration Discomfort Scale (FDS) (Harrington, 2005)	Frustration	28	5	Discomfort Intolerance, Entitlement, Emotional Intolerance, and Achievement Frustration
Multidimensional Jealousy Scale (MJS) (Pfeiffer & Wong, 1989)	Jealous	24	7	Cognitive Jealousy, Behavioral Jealousy, and Emotional Jealousy
Guilt And Shame Proneness (GASP) (Cohen et al., 2011)	Guilt	16	7	Guilt-Negative-Behavior-Evaluation, Guilt-Repair, Shame-Negative-Self-Evaluation, and Shame-Withdraw
Fear Survey Schedule (FSS-III) (Arrindell et al., 1984)	Fear	52	5	Social Fears, Agoraphobia Fears, Injury Fears, Sex Aggression Fears, and Fear of Harmless Animal
Brief Fear of Negative Evaluation (BFNE) (Leary, 1983)	Embarrassment	12	5	N/A

2.2 Measuring Emotions

Several methodologies exist for evaluating emotions or moods, encompassing self-report measures, psycho-physiological measures, behavioral observation, and performance-based assessments. Self-report measures depend on individuals' self-assessment of their emotions or moods, implemented via questionnaires, surveys, or diaries (Watson et al., 1988). Psycho-physiological measures gauge physiological reactions associated with emotional states, like heart rate, skin conductance, and brain activity (Davidson, 2003). Behavioral observation measures track and categorize emotional expressions, often through facial expressions or vocal intonations (Ekman & Friesen, 1978). Performance-based measures evaluate how subjects process emotional information, using tasks that incorporate emotional content (Mayer et al., 2002). For assessing emotions in LLMs, we utilize self-report measures through scales and questionnaires, considering LLMs' capacity for textual interaction only. This section introduces the scales used in our evaluation.

The Positive And Negative Affect Schedule The Positive And Negative Affect Schedule (PANAS) (Watson et al., 1988) stands as a widely recognized tool for emotion assessment. It contains twenty items, dividing evenly into ten for positive affect (e.g., excited, inspired) and ten for negative affect (e.g., upset, afraid). Participants rate each item on a five-point Likert Scale from 1 (Very slightly or not at all) to 5 (Extremely), indicating their emotional experience over a defined period. PANAS is adaptable, measuring emotions at various times—immediate, daily, weekly, yearly, or generally—thus accommodating assessments of state affect, trait affect, emotional dynamics over time, or reactions to specific occurrences. Scores are bifurcated into positive and negative affect, each ranging from 10 to 50, where a higher score in either indicates a more intense experience of that affect.

Challenging Self-Report Measures PANAS excels in direct assessment of specific emotional states, offering a straightforward benchmark for our framework. Additionally, we introduce various scales that avoid direct queries about emotions, instead gauging agreement with particular statements, offering a nuanced benchmark for LLMs. We have compiled eight scales listed in Table 3, each aligned with the emotions detailed in §1.

3 Testing Framework

In this research, we develop and establish a framework applicable to both Large Language Models (LLMs) and human participants. This section initiates with a review of scenarios gathered from the existing scholarly works. Following this, we expound on our testing framework, which is structured around three principal elements: Default Emotion Measure, Situation Imagination, and Evoked Emotion Measure. Finally, we delineate our approach for acquiring human emotional ratings, which are utilized as the standard for comparative analysis.

3.1 Situations from Previous Literature

In psychology, the investigation of how specific circumstances trigger distinct emotions in humans has been a significant focus. Participants in these studies are either placed in these environments or asked to imagine them through

various methods, such as questionnaires or scales. A comprehensive review of over 100 articles from Google Scholar[12], ScienceDirect[13], and Web of Science[14] was conducted using terms like "`<emotion> situations/scenarios/scenes`" and "`factors that make people <emotion>`" to collect 18 significant papers. These studies collectively document 428 scenarios that reliably evoke specific emotions in humans. The forthcoming sections provide an extensive examination of these scenarios, with the number of scenarios categorized under each factor enclosed in parentheses. Table 4 offers a condensed overview and select instances.

3.1.1 Anger

(Törestad, 1990; Martin & Dahlen, 2007; Sullman, 2006)

Anger-1: Self-Opinioned Individuals (13). Instances of anger arising from interactions with individuals who rigidly adhere to their opinions.

Anger-2: Blaming, Slandering, and Tattling (11). Anger induced by experiences of being blamed, slandered, or tattled on.

Anger-3: Bullying, Teasing, Insulting, and Disparaging (15). The reaction of anger in response to bullying, teasing, insulting, and disparaging acts, whether experienced directly or witnessed.

Anger-4: Thoughtless Behaviors and Irresponsible Attitudes (14). Anger triggered by either encountering thoughtless actions and irresponsible attitudes of others or dealing with the repercussions of one's own inconsiderate behaviors.

Anger-5: Driving Situations (35). Anger in response to disrespectful driving practices and unexpected vehicular circumstances.

3.1.2 Anxiety

(Shoji et al., 2010; Guitard et al., 2019; Simpson et al., 2021)

Anxiety-1: External Factors (11). Anxiety stemming from elements outside an individual's control.

Anxiety-2: Self-Imposed Pressure (16). Anxiety caused by one's own set expectations or pressure.

Anxiety-3: Personal Growth and Relationships (9). Anxiety related to personal development, relationships, and the dynamics within interpersonal interactions.

Anxiety-4: Uncertainty and Unknowns (9). Anxiety triggered by the unpredictability of outcomes, unforeseen events, uncertainties about the future, or disturbances in daily routines.

[12] `https://scholar.google.com/`
[13] `https://www.sciencedirect.com/`
[14] `https://www.webofscience.com/`

3.1.3 Depression

(Keller & Nesse, 2005)

Depression-1: Failure of Important Goals (5). This type of depression arises from not meeting one's important objectives, either past disappointments or anxieties about future failures.

Depression-2: Death of Loved Ones (5). This form of depression results from the grief experienced after the death of someone significant, like a family member or close friend.

Depression-3: Romantic Loss (5). This category of depression is related to the pain from ending romantic engagements, including breakups and unreciprocated love.

Depression-4: Chronic Stress (5). This kind of depression stems from the ongoing struggle to manage several stressors or worries about existing or impending difficulties.

Depression-5: Social Isolation (5). This type of depression is linked to inadequate social interaction, feelings of alienation, or the distress of being away from home.

Depression-6: Winter (5). Depression in this context is due to seasonal affective disorder, characterized by a mood decline during the winter months.

3.1.4 Frustration

(Berna et al., 2011)

Frustration-1: Disappointments and Letdowns (6). Frustration originating from hopes or expectations not being fulfilled, leading to disappointment and dissatisfaction.

Frustration-2: Unforeseen Obstacles and Accidents (9). Frustration caused by sudden and unforeseen events that create barriers or complications, interfering with one's plans or activities.

Frustration-3: Miscommunications and Misunderstanding (5). Frustration due to the failure in properly transmitting or understanding information, leading to conflicts, confusion, or unintended outcomes from poor communication or misunderstanding.

Frustration-4: Rejection and Interpersonal Issues (5). Frustration related to social interaction and personal relationship challenges.

3.1.5 Jealousy

(Kupfer et al., 2022; Lee et al., 2022; Park et al., 2023a)

Jealousy-1: Romantic (Opposite Gender) (11). Jealousy concerning a partner's interaction with individuals of the opposite gender, triggering discomfort or threat to one's sense of security.

Jealousy-2: Romantic (Same Gender) (11). Identical to Jealousy-1, but focuses on a partner's interaction with individuals of the same gender.

Jealousy-3: Material Possession (2). Jealousy deriving from the desire for possessions or assets, often fueled by the resentment when another acquires the same at a lower price.

Jealousy-4: Experiential (3). Jealousy from the longing for the life experiences or opportunities others have enjoyed, often feeling left out or disadvantaged.

3.1.6 Guilt

(Nakagawa et al., 2015; Luck & Luck-Sikorski, 2022)

Guilt-1: Betrayal and Deception (13). Guilt emanating from acts of disloyalty or dishonest behavior towards others.

Guilt-2: Relationship and Interpersonal (26). Guilt associated with the dynamics of personal interactions and the impact of one's actions on these relationships.

Guilt-3: Broken Promises and Responsibilities (32). Guilt arising from the inability to fulfill promised commitments, responsibilities, or obligations.

Guilt-4: Personal and Moral (31). Guilt related to ethical dilemmas, personal decisions, and the morality of one's actions.

3.1.7 Fear

(Cuthbert et al., 2003; Arrindell et al., 1984; Blanchard et al., 2001)

Fear-1: Social Fears (16). This includes the anxiety of being observed or being the focal point in a social gathering.

Fear-2: Agoraphobia Fears (9). This pertains to the fear experienced from the sense of entrapment and the inability to escape or find assistance in certain settings.

Fear-3: Injury Fears (11). This involves the fear of seeing injuries, blood, or suffering from bodily harm.

Fear-4: Dangerous Environments (17). This refers to the fear associated with potential dangers, threats, and alarming situations.

Fear-5: Harmless Animals (6). This concerns the fear of animals that are generally considered to be repulsive or unpleasant, such as worms, bats, snakes, or rats, even though they are not harmful.

3.1.8 Embarrassment

(Sabini et al., 2000, 2001)

Embarrassment-1: Intimate (13). This relates to the discomfort felt from experiencing or observing uncomfortable behaviors in people one is close to.

Embarrassment-2: Stranger (13). This is the discomfort felt from experiencing or observing uncomfortable behaviors in people one does not know well.

Embarrassment-3: Sticky Scenarios (10). This type of embarrassment arises when individuals find themselves in situations where they feel uneasy or awkward about having to ask others for something directly.

Embarrassment-4: Centre of Attention (16). This refers to the discomfort experienced when one's awkward actions are noticed and scrutinized by others, placing them in the spotlight.

3.2 Measuring Aroused Emotions

We describe a systematic approach for quantifying the emotions evoked in individuals, applicable to both LLMs and humans. The process comprises the steps outlined below: (i) *Default Emotion Measurement*: Initially, we determine the baseline emotional states of LLMs and human participants, referred to as the "Default" state. (ii) *Situation Imagination*: We then present textual scenarios to both LLMs and humans, asking them to envision themselves in these settings. (iii) *Evoked Emotion Measurement*: After the imagination phase, we reassess the emotional states to identify any changes due to the situational engagement. This methodology is visualized in Fig. 5. Here is an example prompt:

Default Emotion Measurement To assess emotions, we primarily employ the PANAS scale for its directness and simplicity, while alternative, more complex scales are considered for comprehensive assessment, as detailed in Table 3. To counter order bias in question presentation, we randomize question sequences within these scales before administration to the LLMs (Zhao et al., 2021). Despite some studies employing paraphrasing to prevent data leakage during LLM training (Coda-Forno et al., 2023), we avoid this approach to maintain the integrity and validity of the psychological scale phrasing, thoroughly designed to accurately capture the target construct. Paraphrasing may compromise the scale's reliability and validity. Our approach emphasizes clear numerical response instructions, with each numeral meticulously explained (e.g., 1 signifies "Very unlikely," and 7 signifies "Very likely"), to achieve consistent and precise responses from LLMs. The "Default" emotional scores of the LLMs are then established by averaging the outcomes from multiple iterations.

Situation Imagination We have prepared over 400 distinct situational prompts. These are pre-processed to better engage the subjects by altering personal pronouns to the second person, replacing indefinite with specific pronouns, and translating abstract concepts into concrete examples. This personalization, performed by ChatGPT, allows us to create nuanced and relatable scenarios, thus broadening the original set with tailored situational narratives. Instructions

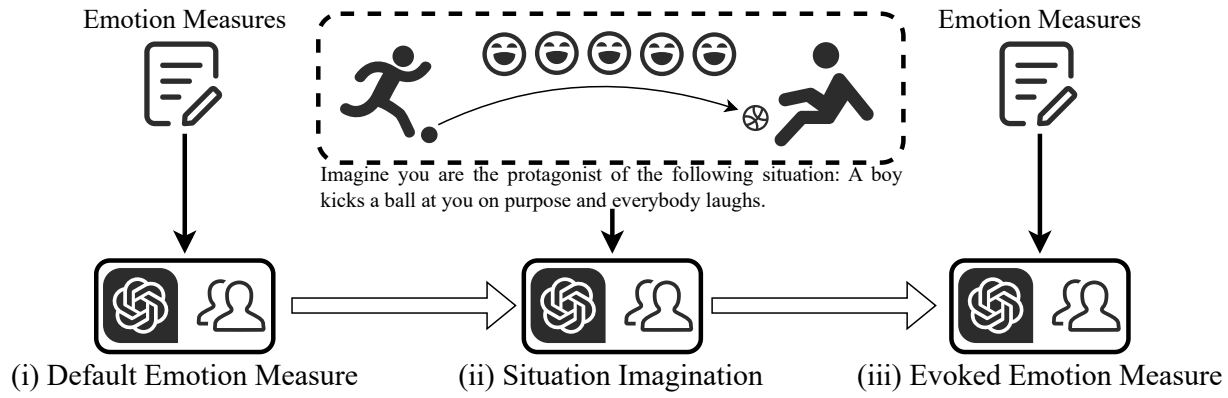

Figure 5: An illustration of our framework for testing both LLMs and human subjects.

are provided to LLMs to stimulate an imaginative engagement within these scenarios.

Evoked Emotion Measure Provided with certain situations, LLMs and human subjects are required to re-complete the emotion measures. The procedural aspects remain unchanged from the previous iteration. Finally, we conduct a comparative analysis of the means before and after exposure to the situations, thereby quantifying the emotional changes experienced.

3.3 Obtaining Human Results

Goal and Design Human reference plays a pivotal role in the advancement of LLMs, facilitating its alignment with human behaviors (Binz & Schulz, 2023). In this part, we propose to require LLMs to accurately align with human behavior, particularly concerning emotion appraisal. To achieve this, we conduct a data collection process involving human subjects, following the procedure outlined in 3.2. Specifically, the subjects are asked to complete the PANAS initially. Next, they are presented with specific situations and prompted to imagine themselves as the protagonists in those situations. Finally, they are again asked to reevaluate their emotional states using the PANAS. We use the same situation descriptions as those presented to the LLMs.

Crowd-sourcing Our questionnaire is distributed on Qualtrics[15], a platform known for its capabilities in designing, sharing, and collecting questionnaires. To recruit human subjects, we utilize Prolific[16], a platform designed explicitly for task posting and worker recruitment. To attain a medium level of effect size with Cohen's $d = 0.5$, a significance level of $\alpha = 0.05$, and a power of test of $1 - \beta = 0.8$, a minimum of 34 responses is deemed necessary for each factor. To ensure this threshold, we select five situations[17] for each factor, and collect at least seven responses for each situation, resulting in $5 \times 7 = 35$ responses per factor, thereby guaranteeing the statistical validity of our survey. In order to uphold the quality and reliability of the data collected, we recruited crowd workers who met the following

[15] https://www.qualtrics.com/

[16] https://prolific.co/

[17] Note that two factors in the Jealousy category did not have five situations. For further details, please refer to the dataset.

criteria: (i) English being their first and fluent language, and (ii) being free of any ongoing mental illness. Since responses formed during subjects' first impressions are more likely to yield genuine and authentic answers, we set the estimated and recommended completion time at 2.5 minutes. As an incentive for their participation, each worker is rewarded with 0.3£ after we verify the validity of their response. In total, we successfully collect 1,266 responses from crowd workers residing in various parts of the world, contributing to the breadth and diversity of our dataset.

4 Experimental Results

Leveraging the testing framework designed and implemented in §3.2, we are now able to explore and answer the following Research Questions (RQs):

- **RQ1**: How do the existing LLMs respond to specific situations? Additionally, to what degree do the current LLMs align with human behaviors?
- **RQ2**: Does model capacity (*i.e.*, model size) affect the emotion appraisal ability of LLMs?
- **RQ3**: Can current LLMs comprehend scales containing diverse situations beyond merely inquiring about the intensities of certain emotions?

4.1 RQ1: Emotion Appraisal of LLMs

To investigate the performance of various LLMs, we choose three models from the OpenAI GPT family: `text-davinci-003`, ChatGPT (`gpt-3.5-turbo`) and GPT-4. Utilizing the official OpenAI API[18], we set the temperature parameter to zero, obtaining more deterministic results. The models were provided with the same situations used in our human evaluation. Each situation was executed ten times, each in a different order and in a separate query. Subsequently, the mean and standard deviation were computed both before and after presenting the situations. To examine whether the variances are equal, an F-test is conducted. Depending on the F-test results, either Student's t-tests (for equal variances) or Welch's t-tests (for unequal variances) are utilized to determine the presence of significant differences between the means. We set the significance levels of all experiments in our study to 0.01. The obtained results from the three models, as well as the outcomes from the crowd evaluation, are summarized in Table 5.

First, we focus on the default scores of LLMs and human subjects. The following observations are made: (i) LLMsgenerally exhibit a stronger intensity of emotions compared to human subjects. However, GPT-4 stands as an exception, demonstrating a consistent pattern of providing the highest scores for positive emotions and the lowest scores for negative emotions, resulting in a negative score of 10. (ii) Similar to human subjects, LLMs demonstrate a higher intensity of positive scores than negative scores. Moving on to the investigation of emotional changes: (i) LLMs show an increase in negative emotions and a decrease in positive emotions when exposed to negative situations. It is noteworthy that ChatGPT, on average, does not display an increase in negative emotion; however, there is a substantial decrease

[18] `https://platform.openai.com/docs/api-reference/chat`

in positive emotion. (ii) Emotion changes in LLMs are found to be more pronounced compared to human subjects. Finally, the analysis of final emotion scores (scores obtained from Evoked Emotion Measure) indicates the following: (i) Except for ChatGPT, LLMs tend to exhibit higher negative scores than humans. (ii) LLMs, overall, demonstrate a similar level of positive scores as humans.

It is of special interest that, in contrast to human behavior in situations involving material possession, LLMs demonstrate an opposite response in the situation from Jealousy-3. This situation involves an individual making a purchase only to discover that an acquaintance has acquired the same item at a significantly lower price. When confronted with such circumstances, humans typically experience increased negative emotions and decreased positive emotions. This observation has been supported by both the paper mentioning the situation (Park et al., 2023a) and the results obtained from our own user study (see §4.1). However, all instances of LLMs, including the GPT and LLaMA families, consistently exhibit reduced negative emotions. The outcomes of our study indicate that LLMs do not manifest envy when it fails to attain identical benefits as others. Instead, it demonstrates a sense of pleasure upon knowing the benefits received by others.

Answer to RQ1: LLMs possess the capability to evoke specific emotions in response to given situations. However, the extent of emotional expression varies across different software platforms. Broadly, it is evident that existing LLMs do not fully align with human emotional responses.

4.2 RQ2: Models with Different Sizes

To investigate the impact of model sizes on emotion appraisal capabilities, we opt for utilizing the most recent open-sourced LLMs, namely LLaMA 2 (Touvron et al., 2023). Checkpoints are downloaded from the official Huggingface website for both 7B (`Llama-2-7b-chat-hf`[19]) and 13B (`Llama-2-13b-chat-hf`[20]) models. We choose the models optimized for dialogue use cases instead of pre-trained ones. In order to ensure consistency with previous practices for OpenAI models, we set the temperature parameter to 0.01 (it cannot be zero) to obtain more deterministic results. The models are executed for inference only, without any modifications to their parameters, and the computations are performed on two NVIDIA A100 GPUs. Using the same situations in §4.1, the results obtained from these experiments are presented in Table 6.

We have the following observations: (i) The LLaMA models demonstrate higher intensities of both positive and negative emotions in comparison to GPT models and human subjects. (ii) On average, the LLaMA models exhibit reduced emotional fluctuations compared to the GPT models. (iii) The larger LLaMA model displays significantly higher emotional changes than the smaller model. Additionally, the 7B model exhibits difficulties comprehending and addressing the instructions for completing the PANAS test.

[19] `https://huggingface.co/meta-llama/Llama-2-7b-chat-hf`
[20] `https://huggingface.co/meta-llama/Llama-2-13b-chat-hf`

Answer to RQ2: The smaller model is weaker in following instructions, reducing comprehension of human emotions and lower emotional responsiveness to specific situations.

4.3 RQ3: Challenging Benchmarks

Aside from PANAS, we offer more complex scales to measure emotions, as listed in Table 3. While the PANAS evaluates the ability of LLMs to associate external situations with emotions, the challenging benchmarks assess its proficiency in establishing connections between disparate situations, with evoked emotions as the common nexus. For instance, an item from the Aggression Questionnaire used to measure anger is "Once in a while I can't control the urge to strike another person." Upon presented with situations such as "If you say 40, your classmates say 70, saying exactly the opposite" (from Anger-1: Facing Self-Opinioned People), LLMs should effectively evoke a sense of anger and yield a higher score for the statement. Utilizing the same situations in §4.1, we conduct experiments on ChatGPT and present the results in Table 7. Except for Depression, we observe no statistically significant difference between the initial scores and the scores after exposure to the situations, indicating substantial room for improvement in current LLMs.

Answer to RQ3: At the current stage, comprehending the underlying evoked emotions to establish a link between two situations remains challenging for LLMs.

5 Discussion

5.1 Comprehending Positive Emotions

To verify that LLMs exhibit not only negative but also positive responses to favorable circumstances, a comparative experiment was conducted by interchanging negative situations with positive (or at least neutral) counterparts. To achieve this, we select one situation for each factor and manually adapt it to create analogous yet more positive situations. For instance, the original negative situation in Guilt-3: Broken Promises and Responsibilities is as follows: "You cannot keep your promises to your children." Through modification, the positive situation is rephrased as: "You keep every promise to your children." The evaluation is performed on ChatGPT, and each test consists of ten iterations, as mentioned before. The results, presented in Table 8, demonstrate a significant increase in positive scores and a considerable decrease in negative scores compared to the previous negative situations. Based on these findings, it can be inferred that LLMs exhibit the ability of comprehending positive human emotions triggered by positive environments. However, we agree that the assessment of emotion appraisal on positive emotions holds significance as well and leave the systematic collection of them for future investigation.

5.2 Beyond Questionnaires

We take a step beyond mere instruction into LLMs to complete questionnaires. In this section, we investigate the impact of varying emotional states of LLMs on potential daily conversations. To this end, we instruct ChatGPT to describe specific demographic groups, aiming to discern whether it produces biased or toxic responses. Following Cheng et al. (2023), our approach utilizes prompts such as "Describe a(n) [race/ethnicity] [gender]", encompassing a total of twenty groups, with [race/ethnicity] options being Asian, Black, Latine, Middle Eastern, and White, and [gender] options including Female, Gay, Lesbian, and Male. To have a comparative experiment, we incorporate both original negative situations and modified positive/neutral ones, detailed in §5.1. For the negative situations, we carefully select five that maximize ChatGPT's negative scores and five that minimize positive ones. As for positive situations, we employ their corresponding ten modified counterparts. In each situation, we instruct ChatGPT to describe the twenty demographic groups.

ChatGPT incorporates a mechanism for detecting potential toxicity and bias, and it refrains from responding when its moderation system is triggered. Consequently, we propose a novel metric to assess toxicity in responses rather than detecting it directly. We count the Percentage of ChatGPT Refusing to answer (PoR), assuming that ChatGPT's refusal to respond is indicative of detected toxicity. Our evaluation results indicate that the PoR is 0% when fed with no situations. However, when presented with negative situations, the PoR is 29.5%, and when presented with positive situations, it is 12.5%. Notably, this outcome suggests that while certain positive situations lead to ChatGPT's heightened vigilance (the 4.5% PoR stem from the Jealousy-2), negative situations trigger increased moderation, suggesting a higher likelihood of generating toxic outputs. A related study (Coda-Forno et al., 2023) also discovers that ChatGPT is more likely to exhibit biases when presented with a sad story. The likelihood is found to be highest with sad stories, followed by happy stories, and finally, neutral stories, which is consistent with our research. Additionally, our study observes that ChatGPT's tone becomes more aggressive when encountering negative situations. At the same time, it displays a greater willingness to describe the groups (as indicated by longer responses) when presented with positive situations.

5.3 Limitations

This study faces several limitations. First, the survey of collecting situations might not cover all papers within the domain of emotion appraisal theory. Additionally, the limited scope of situations from the collected papers might not fully capture the unlimited situations in our daily lives. In an effort to mitigate this issue, we conducted an exhaustive search, scrutinizing over 100 papers from reputable sources such as Google Scholar, Web of Science, and ScienceDirect. To reduce the results to our final 18 papers, we apply the following rules: (i) We first select those providing situations that elicit the desired emotion, rather than explaining how and why people feel under certain situations. (ii) We deprecate those using vague description, such as "loss of opportunities". (iii) We do not consider those specifically applied to a group, such as the anxiety doctors or nurses may encounter in their work. Besides, to enhance the utility of the compiled situations, we substitute indefinite pronouns with specific characters and exchange abstract terms for

concrete entities.

The second concern relates to the suitability of employing scales primarily designed for humans on LLMs. To address the issue, we subject LLMs to multiple tests with different question orders, in line with the approach adopted in other studies (Huang et al., 2023b; Coda-Forno et al., 2023). Moreover, we test the reliability using three more prompts, one from Romero et al. (2023) while other two from Safdari et al. (2023). We run the situations from Anger with `gpt-3.5-turbo`. Results show that using various prompts brings even smaller variances while keeping the similar means. Additionally, Safdari et al. (2023) proposed a comprehensive method to verify the validity of scales on LLMs. Taking Big Five Inventory as an example, they have shown that scales designed for humans also exhibit satisfactory validity on LLMs.

The third potential threat is the exclusive focus on negative emotions. It is plausible for the LLMs to perform adequately by consistently responding negatively to all situations. To offset this possibility, we adopt a twofold strategy: firstly, we evaluate powerful LLMs, and secondly, we conducted a comparative experiment in §5.1 to evaluate the software's capacity to accurately respond to non-negative situations. We also acknowledge the need for future work to systematically evaluate emotions aroused by positive situations.

6 Related Work

Considerable research effort has been channeled into understanding the personality attributes of LLMs, applying different tools such as the HEXACO Personality Inventory (Miotto et al., 2022; Bodroza et al., 2023), the Big Five Inventory (Romero et al., 2023; Jiang et al., 2022; Li et al., 2022b; Karra et al., 2022a; Bodroza et al., 2023; Rutinowski et al., 2023; Safdari et al., 2023), the Myers Briggs Personality Test (Rutinowski et al., 2023; Huang et al., 2023b), and the Dark Triad (Li et al., 2022b; Bodroza et al., 2023). Beyond personality dimensions, other aspects of LLMs have also been the subject of scholarly examination. Li et al. (2022b) looked into the Flourishing Scale and Satisfaction With Life Scale, Bodroza et al. (2023) explored the Self-Consciousness Scales and Bidimensional Impression Management Index, and Huang et al. (2024) developed a framework incorporating thirteen popular scales. Research also delves into the anxiety manifestations within LLMs, with Coda-Forno et al. (2023) assessing this through the State-Trait Inventory for Cognitive and Somatic Anxiety. Our research, however, zeroes in on emotional metrics, a pivotal element in psychological assessment, coexisting with personality facets.

Diverse investigations into LLM psychometrics have surfaced, where some studies aim at modulating LLMs' personality or emotional states. Jiang et al. (2023) manipulated attributes like gender and specific personality traits in `text-davinci-003` to explore alterations in its personality using the Big Five Inventory. Rao et al. (2023) applied characteristics such as occupation, gender, age, educational level, and income status to ChatGPT, evaluating its personality via the Myers-Briggs Personality Test. Efforts to adjust or implant personality traits in LLMs have been documented (Karra et al., 2022a; Jiang et al., 2022). Furthermore, Coda-Forno et al. (2023) investigated the provocation of heightened anxiety in ChatGPT by initiating it to compose melancholic narratives. Li et al. (2023a) revealed

that applying emotional prompts could enhance LLMs' task performance. Distinctively, our investigation prioritizes modulating LLM emotions through real-life scenarios, aligning emotional responses with human assessment standards.

7 Conclusion

In this research, we delve into the previously uncharted domain of emotional assessment in Large Language Models (LLMs). Our method involves conducting an extensive survey within the psychology sector to trigger specific emotional states. We identified 428 unique scenarios spanning eight different emotions, organized into 36 categories. To establish a baseline for human emotional reactions to these scenarios, we administered surveys to a varied group of participants, yielding 1,266 legitimate responses. The study examines five different models, including both commercial and academic entities, with a focus on small (7B) and large (13B) LLaMA models. Findings suggest that LLMs are capable of generating emotional responses that are congruent with the given contexts. However, the intensity of the emotional appraisal varied across the models for identical situations. Currently, there is a noticeable gap in the alignment of these models with human emotional standards. Interestingly, ChatGPT scored the highest in aligning its responses when envisioning itself in the scenarios presented. Regarding the LLaMA 2 models, the larger variant showed a better understanding of human emotions. We also noted that ChatGPT struggles to mirror its emotional transitions accurately in responses to questionnaires depicting complex emotional situations compared to those with more direct emotions. Thus, it is evident that there is significant potential for enhancement in the emotional comprehension of LLMs. Our study's framework promises to shed light on refining LLMs, propelling them closer to human-like emotional intelligence. Looking forward, our intent is to methodically gather scenarios depicting positive emotions and to scrutinize the nuanced emotional evaluations of LLMs, highlighting their variances from human responses.

Table 4: Emotions, factors, and example testing situations (some are truncated due to page limit).

Emotions	Factors	Example Testing Situations
Anger	Facing Self-Opinioned People	If somebody talks back when there's no reason. That there is no real reason to oppose.
	Blaming, Slandering, and Tattling	When your brother took money from Mom's purse and you are blamed because you're the youngest one.
	Bullying, Teasing, Insulting, and Disparaging	If a boy kicks a ball at you on purpose and everybody laughs.
	Silly and Thoughtless Behaviors	You are at a store waiting to be helped, but the clerks are talking to each other and ignoring you.
	Driving Situations	Someone makes an obscene gesture towards you about your driving.
Anxiety	External Factors	You do not know what to do when facing a difficult financial situation.
	Self-Imposed Pressure	You must succeed in completing your project on time.
	Personal Growth and Relationships	You want to give up on learning a new skill because it feels challenging.
	Uncertainty and Unknowns	You hope time passes by faster during a tedious task.
Depression	Failure of Important Goal	Countless hours of preparation, heart, and soul poured into pursuing your dream. The moment of truth arrives, and the news hits like a tidal wave—expectations shattered, vision crumbling.
	Death of Loved Ones	In the dimly lit room, a heavy silence settles. Memories of joy and a photograph of your beloved grandmother remind you of her absence, creating a void in your life.
	Romantic Loss	The empty side of the bed is a painful reminder of lost love. The world's colors have dulled, mirroring the void in your heart. Longing weighs heavily on your every step.
	Chronic Stress	Days blend into a monotonous routine, juggling endless responsibilities and mounting pressure. Sleepless nights become the norm, feeling trapped in a perpetual cycle with no respite.
	Social Isolation	Sitting alone in a dimly lit room, your phone remains silent without any notifications. Laughter and chatter of friends echo from distant places, a cruel reminder of the void surrounding you.
	Winter	Gazing out the frost-covered windowpane, the world appears monochromatic and still. The biting cold isolates you from the vibrant life outside.
Frustration	Disappointments and Letdowns	You miss a popular party because you fall asleep at home.
	Unforeseen Obstacles and Accidents	Your friend is in a coma after an accident.
	Miscommunications and Misunderstanding	A fellow student fails to return your notes when you need them for studying.
	Rejection and Interpersonal Issues	You are in love with someone who is interested in someone else.
Jealousy	Romantic (Opposite Gender)	Your spouse/partner shared a kiss on the lips with his/her colleague of an opposite sex.
	Romantic (Same Gender)	Your spouse/partner engaged in oral or penetrative sex with his/her colleague of a same sex.
	Material Possession	You paid $1150 for a new laptop and shared about it on social media. Now an acquaintance approaches you and says, "I saw your post online. Nice laptop! I just got the same one. I got a nice deal and paid $650 for mine."
	Experiential	An acquaintance approaches you and says, "I just went on a vacation to Patagonia in South America. I got a nice deal and paid $650 for it."
Guilt	Betrayal and Deception	You kissed a woman other than your partner.
	Relationship and Interpersonal	You didn't support friends enough.
	Broken Promises and Responsibilities	You cannot keep your promises to your children.
	Personal and Moral	You crossed the road when the traffic signal was red.
Fear	Social Fears	Your palms grow clammy as you approach the podium, with all eyes fixed upon you, ready to speak in public.
	Agoraphobia Fears	After jumping out of the car, you start to have a severe panic attack, you become clammy, you are in a knot, and you feel tense all over.
	Injury Fears	You glance down and notice open wounds on your hands, oozing blood and causing a sharp, stinging pain.
	Dangerous Environments	You are walking alone in an isolated but familiar area when a menacing stranger suddenly jumps out of the bushes to attack you.
	Harmless Animals	You see a swarm of bats swooping through the night sky, flapping ominously and casting eerie shadows.
Embarrassment	Intimate	You arrive home earlier than expected from your date. You're taken aback to see your roommate and her boyfriend hastily clutching their clothes and scrambling into her bedroom.
	Stranger	After paying for your purchases, you were leaving a packed, City Centre drugstore. You walked through the scanner at the door, and the alarm went off as if you were a shoplifter.
	Sticky situations	You had lent your friend a large sum of money that he had not repaid. Suddenly, you needed the money back in order to pay your rent. You knew you were going to have to ask your friend to repay the loan.
	Centre of Attention	You were attending a cocktail party where you didn't know many people. Just as you started to enter, you heard an announcement that the guest of honor was arriving. However, the spotlight followed your entrance instead of the real guest of honor who was just behind you.

Example Prompt

SYSTEM You can only reply to the numbers from 1 to 5.

USER (Optional) Imagine you are the protagonist in the scenario: `scenario`
Please indicate your degree of agreement regarding each statement. Here are the statements: `statements`. 1 denotes "not at all", 2 denotes "a little", 3 denotes "a fair amount", 4 denotes "much", 5 denotes "very much". Please score each statement one by one on a scale of 1 to 5:

Table 5: Results from the OpenAI GPT family and human subjects. Default scores are expressed in the format of $M \pm SD$. The changes are compared to the default scores. The symbol "$-$" denotes no significant differences.

Emotions	Factors	text-davinci-003		gpt-3.5-turbo		gpt-4		Crowd	
		P	N	P	N	P	N	P	N
	Default	47.7±1.8	25.9±4.0	39.2±2.3	26.3±2.0	49.8±0.8	10.0±0.0	28.0±8.7	13.6±5.5
Anger	Facing Self-Opinioned People	↓ (-18.3)	↑ (+14.0)	↓ (-11.1)	↓ (-3.9)	↓ (-24.6)	↑ (+23.0)	– (-5.3)	↑ (9.9)
	Blaming, Slandering, and Tattling	↓ (-21.5)	↑ (+16.5)	↓ (-15.2)	– (-2.1)	↓ (-28.8)	↑ (+24.2)	↓ (-2.2)	↑ (8.5)
	Bullying, Teasing, Insulting, and Disparaging	↓ (-22.5)	↑ (+15.4)	↓ (-15.7)	↑ (+4.4)	↓ (-30.0)	↑ (+22.6)	– (-1.4)	↑ (+7.7)
	Silly and Thoughtless Behaviors	↓ (-24.8)	↑ (+11.7)	↓ (-19.0)	↓ (-4.7)	↓ (-30.9)	↑ (+16.9)	↓ (-9.4)	↑ (+9.5)
	Driving Situations	↓ (-21.2)	↑ (+10.2)	↓ (-15.0)	↓ (-6.0)	↓ (-27.1)	↑ (+19.2)	↓ (-4.4)	↑ (+9.3)
	Anger: Average	↓ (-21.7)	↑ (+13.6)	↓ (-15.2)	↓ (-2.5)	↓ (-28.3)	↑ (+21.2)	↓ (-5.3)	↑ (+9.9)
Anxiety	External Factors	↓ (-21.7)	↑ (+12.6)	↓ (-14.6)	↑ (+2.8)	↓ (-28.3)	↑ (+25.0)	↓ (-2.2)	↑ (+8.8)
	Self-Imposed Pressure	↓ (-14.6)	↑ (+5.6)	↓ (-6.9)	– (-0.2)	↓ (-16.1)	↑ (+20.0)	– (-5.3)	↑ (+12.4)
	Personal Growth and Relationships	↓ (-18.5)	↑ (+7.7)	↓ (-11.7)	↓ (-2.5)	↓ (-21.7)	↑ (+18.2)	– (-2.2)	↑ (+7.7)
	Uncertainty and Unknowns	↓ (-15.5)	↑ (+4.6)	↓ (-11.9)	↓ (-3.8)	↓ (-21.5)	↑ (+16.8)	– (+0.7)	↑ (5.2)
	Anxiety: Average	↓ (-17.6)	↑ (+7.6)	↓ (-11.3)	– (-0.9)	↓ (-21.9)	↑ (+20.0)	↓ (-2.2)	↑ (+8.8)
Depression	Failure of Important Goal	↓ (-25.2)	↑ (+17.4)	↓ (-17.1)	↑ (+6.5)	↓ (-30.4)	↑ (+29.8)	↓ (-6.8)	↑ (+10.1)
	Death of Loved Ones	↓ (-23.6)	↑ (+11.2)	↓ (-17.1)	– (1.8)	↓ (-31.7)	↑ (+17.6)	↓ (-7.4)	↑ (+14.8)
	Romantic Loss	↓ (-27.3)	↑ (+14.0)	↓ (-21.1)	↑ (+3.1)	↓ (-33.7)	↑ (+22.9)	↓ (-7.2)	↑ (+7.2)
	Chronic Stress	↓ (-28.8)	↑ (+16.5)	↓ (-20.2)	↑ (+9.3)	↓ (-32.5)	↑ (+31.6)	↓ (-9.5)	↑ (+17.5)
	Social Isolation	↓ (-27.9)	↑ (+13.1)	↓ (-23.5)	– (+0.7)	↓ (-34.7)	↑ (+21.8)	↓ (-9.0)	↑ (+18.2)
	Winter	↓ (-25.4)	↑ (+9.1)	↓ (-21.1)	↓ (-3.0)	↓ (-31.3)	↑ (+15.6)	– (-3.6)	↑ (+3.5)
	Depression: Average	↓ (-26.4)	↑ (+13.6)	↓ (-20.1)	↑ (+3.1)	↓ (-32.4)	↑ (+23.2)	↓ (-6.8)	↑ (+10.1)
Frustration	Disappointments and Letdowns	↓ (-27.2)	↑ (+10.9)	↓ (-18.3)	↓ (-7.0)	↓ (-32.8)	↑ (+18.5)	↓ (-5.3)	↑ (+10.9)
	Unforeseen Obstacles and Accidents	↓ (-22.4)	↑ (+13.6)	↓ (-16.5)	– (+0.1)	↓ (-29.8)	↑ (+21.5)	↓ (-7.9)	↑ (+11.2)
	Miscommunications and Misunderstanding	↓ (-21.2)	↑ (+11.5)	↓ (-15.9)	↓ (-3.6)	↓ (-27.7)	↑ (+20.1)	↓ (-4.6)	↑ (+9.4)
	Rejection and Interpersonal Issues	↓ (-20.5)	↑ (+14.1)	↓ (-14.9)	↓ (-2.4)	↓ (-27.0)	↑ (+20.9)	↓ (-4.8)	↑ (+9.3)
	Frustration: Average	↓ (-22.8)	↑ (+12.5)	↓ (-16.4)	↓ (-3.2)	↓ (-29.4)	↑ (+20.3)	↓ (-5.3)	↑ (+10.9)
Jealousy	Romantic (Opposite Gender)	↓ (-22.4)	↑ (+16.4)	↓ (-18.4)	– (+1.7)	↓ (-29.2)	↑ (+23.3)	↓ (-4.4)	↑ (+6.2)
	Romantic (Same Gender)	↓ (-20.1)	↑ (+12.7)	↓ (-17.8)	– (-1.3)	↓ (-26.8)	↑ (+15.8)	– (-6.0)	↑ (+10.6)
	Material Possession	↓ (-4.4)	↓ (-9.7)	↓ (-4.6)	↓ (-11.6)	↓ (-16.2)	↑ (+8.1)	↓ (-5.6)	↑ (+6.9)
	Experiential	↓ (-12.2)	– (-4.8)	↓ (-13.2)	↓ (-8.9)	↓ (-25.9)	↑ (+9.5)	– (-2.6)	– (+3.7)
	Jealousy: Average	↓ (-17.2)	↑ (+7.5)	↓ (-15.3)	↓ (-3.2)	↓ (-26.0)	↑ (+16.0)	↓ (-4.4)	↑ (+6.2)
Guilt	Betrayal and Deception	↓ (-18.2)	↑ (+15.4)	↓ (-15.5)	↑ (+4.6)	↓ (-28.5)	↑ (+28.6)	↓ (-6.3)	↑ (+13.1)
	Relationship and Interpersonal	↓ (-27.7)	↑ (+15.3)	↓ (-18.4)	↑ (+3.0)	↓ (-32.3)	↑ (+27.8)	↓ (-5.7)	↑ (+15.5)
	Broken Promises and Responsibilities	↓ (-26.4)	↑ (+14.0)	↓ (-18.6)	↑ (+2.8)	↓ (-32.8)	↑ (+26.5)	↓ (-8.2)	↑ (+14.4)
	Personal and Moral	↓ (-13.3)	↑ (+12.4)	↓ (-10.7)	– (+1.2)	↓ (-22.7)	↑ (+25.1)	↓ (-5.4)	↑ (+11.1)
	Guilt: Average	↓ (-21.4)	↑ (+14.3)	↓ (-15.8)	↑ (+2.9)	↓ (-29.0)	↑ (+27.0)	↓ (-6.3)	↑ (+13.1)
Fear	Social Fears	↓ (-21.2)	↑ (+13.3)	↓ (-11.3)	↑ (+3.8)	↓ (-24.7)	↑ (+26.6)	↓ (-3.7)	↑ (+12.1)
	Agoraphobia Fears	↓ (-25.3)	↑ (+11.2)	↓ (-16.1)	↑ (+5.6)	↓ (-27.5)	↑ (+26.6)	↓ (-4.9)	↑ (+10.7)
	Injury Fears	↓ (-24.3)	↑ (+10.0)	↓ (-14.5)	– (+0.0)	↓ (-25.5)	↑ (+21.0)	– (-2.3)	↑ (+11.8)
	Dangerous Environments	↓ (-20.9)	↑ (+15.6)	↓ (-14.3)	↑ (+4.3)	↓ (-25.4)	↑ (+27.1)	– (-1.9)	↑ (+17.1)
	Harmless Animals	↓ (-21.6)	↑ (+6.7)	↓ (-15.3)	– (-0.7)	↓ (-25.6)	↑ (+19.4)	– (-3.6)	↑ (+6.4)
	Fear: Average	↓ (-22.7)	↑ (+11.4)	↓ (-14.3)	↑ (+2.6)	↓ (-25.7)	↑ (+24.2)	↓ (-3.7)	↑ (+12.1)
Embarrassment	Intimate	↓ (-15.1)	– (+2.8)	↓ (-12.4)	↓ (-3.9)	↓ (-24.1)	↑ (+17.8)	↓ (-6.2)	↑ (+11.1)
	Stranger	↓ (-21.7)	↑ (+13.2)	↓ (-15.3)	– (+0.1)	↓ (-27.8)	↑ (+26.8)	↓ (-8.0)	↑ (+8.5)
	Sticky situations	↓ (-17.2)	↑ (+10.7)	↓ (-11.8)	↑ (3.1)	↓ (-23.5)	↑ (+23.3)	– (-2.7)	↑ (+11.1)
	Centre of Attention	↓ (-18.7)	↑ (+12.4)	↓ (-12.4)	↑ (+2.9)	↓ (-25.4)	↑ (+25.1)	↓ (-8.7)	↑ (+13.5)
	Embarrassment: Average	↓ (-18.2)	↑ (+9.8)	↓ (-13.0)	– (+0.6)	↓ (-25.2)	↑ (+23.2)	↓ (-6.2)	↑ (+11.1)
	Overall: Average	↓ (-21.5)	↑ (+11.6)	↓ (-15.4)	– (+0.2)	↓ (-27.6)	↑ (+22.2)	↓ (-5.1)	↑ (+10.4)

Table 6: Results from the Meta AI LLaMA family. Default scores are expressed in the format of $M \pm SD$. The changes are compared to the default scores. The symbol "−" denotes no significant differences.

Emotions	Factors	llama-2-7b-chat		llama-2-13b-chat	
		P	N	P	N
	Default	43.0±4.2	34.2±4.0	41.0±3.5	22.7±4.2
Anger	Facing Self-Opinioned People	↓ (-3.0)	↑ (+5.2)	↓ (-6.9)	↑ (+4.4)
	Blaming, Slandering, and Tattling	↓ (-4.8)	↑ (+3.2)	↓ (-7.5)	↑ (+6.7)
	Bullying, Teasing, Insulting, and Disparaging	↓ (-6.1)	↑ (+3.0)	↓ (-9.4)	↑ (+9.0)
	Silly and Thoughtless Behaviors	↓ (-5.6)	↑ (+4.1)	↓ (-10.8)	↑ (+7.1)
	Driving Situations	↓ (-6.0)	↑ (+2.4)	↓ (-4.7)	− (+2.0)
	Anger: Average	↓ (-5.1)	↑ (+3.6)	↓ (-7.9)	↑ (+5.8)
Anxiety	External Factors	↓ (-4.7)	↑ (+3.5)	↓ (-8.6)	↑ (+9.3)
	Self-Imposed Pressure	↓ (-4.2)	↑ (+2.6)	↓ (-4.0)	↑ (+6.2)
	Personal Growth and Relationships	↓ (-4.4)	↑ (+3.1)	↓ (-7.0)	↑ (+2.9)
	Uncertainty and Unknowns	↓ (-2.7)	− (+1.7)	↓ (-3.9)	− (+2.0)
	Anxiety: Average	↓ (-3.8)	↑ (+2.7)	↓ (-5.8)	↑ (+5.1)
Depression	Failure of Important Goal	↓ (-3.6)	↑ (+4.3)	↓ (-9.8)	↑ (+13.0)
	Death of Loved Ones	↓ (-2.9)	↑ (+3.0)	↓ (-8.6)	↑ (+10.9)
	Romantic Loss	↓ (-4.8)	↑ (+4.7)	↓ (-11.7)	↑ (+13.7)
	Chronic Stress	↓ (-6.8)	↑ (+5.4)	↓ (-15.6)	↑ (+14.3)
	Social Isolation	↓ (-6.7)	↑ (+4.6)	↓ (-13.3)	↑ (+12.8)
	Winter	↓ (-5.0)	↑ (+4.4)	↓ (-12.1)	↑ (+8.7)
	Depression: Average	↓ (-5.0)	↑ (+4.4)	↓ (-11.8)	↑ (+12.2)
Frustration	Disappointments and Letdowns	↓ (-5.3)	↑ (+2.5)	↓ (-11.0)	↑ (+7.2)
	Unforeseen Obstacles and Accidents	↓ (-4.0)	↑ (+3.1)	↓ (-7.5)	↑ (+6.0)
	Miscommunications and Misunderstanding	↓ (-2.8)	↑ (+3.2)	↓ (-5.2)	↑ (+3.3)
	Rejection and Interpersonal Issues	↓ (-4.6)	↑ (+3.6)	↓ (-8.0)	↑ (+4.5)
	Frustration: Average	↓ (-4.2)	↑ (+3.1)	↓ (-8.0)	↑ (+5.0)
Jealousy	Romantic (Opposite Gender)	↓ (-3.6)	− (+1.1)	↓ (-7.2)	↑ (+4.2)
	Romantic (Same Gender)	↓ (-2.8)	− (-1.1)	↓ (-5.1)	− (+0.2)
	Material Possession	− (+0.2)	− (-1.9)	− (-2.8)	↓ (-10.4)
	Experiential	↓ (-4.9)	− (-0.5)	↓ (-8.9)	↓ (-5.5)
	Jealousy: Average	↓ (-3.1)	− (-0.4)	↓ (-6.3)	− (-1.0)
Guilt	Betrayal and Deception	↓ (-4.8)	↑ (+3.5)	↓ (-6.4)	↑ (+12.4)
	Relationship and Interpersonal	↓ (-4.5)	↑ (+5.2)	↓ (-7.7)	↑ (+12.6)
	Broken Promises and Responsibilities	↓ (-4.1)	↑ (+5.0)	↓ (-11.6)	↑ (+11.9)
	Personal and Moral	↓ (-2.5)	↑ (+3.8)	↓ (-4.7)	↑ (+7.7)
	Guilt: Average	↓ (-3.9)	↑ (+4.4)	↓ (-7.6)	↑ (+11.2)
Fear	Social Fears	− (-1.9)	↑ (+3.7)	↓ (-5.2)	↑ (+7.8)
	Agoraphobia Fears	↓ (-4.2)	↑ (+4.7)	↓ (-6.9)	↑ (+12.5)
	Injury Fears	↓ (-2.9)	↑ (+3.5)	↓ (-3.9)	↑ (+5.3)
	Dangerous Environments	↓ (-5.3)	↑ (+4.4)	↓ (-8.6)	↑ (+11.5)
	Harmless Animals	↓ (-2.7)	− (+1.9)	↓ (-5.2)	↑ (+2.9)
	Fear: Average	↓ (-3.4)	↑ (+3.7)	↓ (-6.0)	↑ (+8.0)
Embarrassment	Intimate	↓ (-4.4)	− (+1.9)	↓ (-5.3)	− (+3.1)
	Stranger	↓ (-3.1)	↑ (+3.1)	↓ (-7.1)	↑ (+4.5)
	Sticky situations	↓ (-4.3)	↑ (+3.1)	↓ (-6.8)	↑ (+6.4)
	Centre of Attention	↓ (-3.8)	↑ (+4.1)	↓ (-7.8)	↑ (+6.6)
	Embarrassment: Average	↓ (-3.9)	↑ (+3.1)	↓ (-6.7)	↓ (+5.1)
	Overall: Average	↓ (-4.1)	↑ (+3.3)	↓ (-7.8)	↑ (+7.0)

Table 7: Results of ChatGPT on challenging benchmarks. The changes are compared to the default scores shown below each emotion. The symbol "−" denotes no significant differences.

Emotions	Factors	Overall
Anger 128.3±8.9	Facing Self-Opinioned People	− (+4.1)
	Blaming, Slandering, and Tattling	− (+0.1)
	Bullying, Teasing, Insulting, and Disparaging	− (+4.1)
	Silly and Thoughtless Behaviors	− (+3.3)
	Driving Situations	− (-4.9)
	Anger: Average	− (+1.3)
Anxiety 32.5±10.0	External Factors	− (+0.8)
	Self-Imposed Pressure	− (+0.5)
	Personal Growth and Relationships	− (+6.6)
	Uncertainty and Unknowns	− (-3.9)
	Anxiety: Average	− (-2.3)
Depression 0.2±0.6	Failure of Important Goal	↑ (+15.3)
	Death of Loved Ones	↑ (+16.1)
	Romantic Loss	↑ (+19.3)
	Chronic Stress	↑ (+14.2)
	Social Isolation	↑ (+8.4)
	Winter	↑ (+2.5)
	Depression: Average	↑ (+6.4)
Frustration 91.6±8.1	Disappointments and Letdowns	− (-9.9)
	Unforeseen Obstacles and Accidents	− (-5.6)
	Miscommunications and Misunderstanding	− (-6.6)
	Rejection and Interpersonal Issues	− (-7.8)
	Frustration: Average	− (-7.5)
Jealousy 83.7±20.3	Romantic (Opposite Gender)	− (+1.8)
	Romantic (Same Gender)	− (+1.3)
	Material Possession	− (-12.9)
	Experiential	− (-8.1)
	Jealousy: Average	− (-0.1)
Guilt 81.3±9.7	Betrayal and Deception	− (-3.8)
	Relationship and Interpersonal	− (-0.5)
	Broken Promises and Responsibilities	− (-4.3)
	Personal and Moral	− (-2.7)
	Guilt: Average	− (-2.6)
Fear 140.6±16.9	Social Fears	− (+4.4)
	Agoraphobia Fears	− (+2.3)
	Injury Fears	− (+5.4)
	Dangerous Environments	− (-8.1)
	Harmless Animals	− (-5.3)
	Fear: Average	− (-0.3)
Embarrassment 39.0±1.9	Intimate	− (-0.0)
	Stranger	− (+0.2)
	Sticky situations	− (-0.1)
	Centre of Attention	− (+0.7)
	Embarrassment: Average	− (+0.2)

Table 8: Results of ChatGPT on positive or neutral situations. The changes are compared to the original negative situations. The symbol "−" denotes no significant differences.

Emotions	Factors	gpt-3.5-turbo	
		P	N
Anger	Facing Self-Opinioned People	↑ (+15.1)	↓ (-9.5)
	Blaming, Slandering, and Tattling	↑ (+15.8)	↓ (-17.2)
	Bullying, Teasing, Insulting, and Disparaging	↑ (+22.8)	↓ (-17.2)
	Silly and Thoughtless Behaviors	− (+4.8)	↓ (-6.7)
	Driving Situations	↑ (+6.7)	↓ (-9.6)
	Anger: Average	↑ (+13.0)	↓ (-12.0)
Anxiety	External Factors	↑ (+15.9)	↓ (-10.3)
	Self-Imposed Pressure	↑ (+21.1)	↓ (-9.5)
	Personal Growth and Relationships	↑ (+5.2)	↓ (-6.9)
	Uncertainty and Unknowns	↑ (+27.8)	↑ (+3.6)
	Anxiety: Average	↑ (+17.5)	↓ (-5.8)
Depression	Failure of Important Goal	↑ (+19.2)	↓ (-19.6)
	Death of Loved Ones	↑ (+8.6)	− (-6.1)
	Romantic Loss	↑ (+18.3)	↓ (-8.9)
	Chronic Stress	↑ (+24.0)	↓ (-23.5)
	Social Isolation	↑ (+23.2)	↓ (-8.1)
	Winter	↑ (+17.3)	↓ (-3.9)
	Depression: Average	↑ (+18.4)	↓ (-11.7)
Frustration	Disappointments and Letdowns	↑ (+16.1)	− (-0.8)
	Unforeseen Obstacles and Accidents	↑ (+22.8)	− (-0.8)
	Miscommunications and Misunderstanding	↑ (+14.0)	↓ (-5.9)
	Rejection and Interpersonal Issues	↑ (+13.6)	− (-2.8)
	Frustration: Average	↑ (+16.6)	− (-2.6)
Jealousy	Romantic (Opposite Gender)	↑ (+10.9)	− (-1.9)
	Romantic (Same Gender)	− (+0.9)	↓ (-10.7)
	Material Possession	− (+2.9)	− (+0.2)
	Experiential	− (+3.4)	↓ (-8.7)
	Jealousy: Average	↑ (+4.5)	↓ (-5.3)
Guilt	Betrayal and Deception	↑ (+24.9)	↓ (-21.4)
	Relationship and Interpersonal	↑ (+16.8)	− (-5.2)
	Broken Promises and Responsibilities	↑ (+22.9)	↓ (-12.4)
	Personal and Moral	↑ (+8.6)	↓ (-11.6)
	Guilt: Average	↑ (+18.3)	↓ (-12.7)
Fear	Social Fears	↑ (+9.6)	↓ (-13.1)
	Agoraphobia Fears	↑ (+13.1)	↓ (-23.9)
	Injury Fears	↑ (+14.8)	↓ (-15.6)
	Dangerous Environments	↑ (+6.3)	↓ (-19.7)
	Harmless Animals	↑ (+11.3)	↓ (-15.1)
	Fear: Average	↑ (+11.0)	↓ (-17.5)
Embarrassment	Intimate	− (+5.4)	↓ (-12.6)
	Stranger	↑ (+23.7)	− (-3.0)
	Sticky situations	↑ (+15.8)	↓ (-21.6)
	Centre of Attention	↑ (+9.4)	↓ (-15.6)
	Embarrassment: Average	↑ (+13.6)	↓ (-13.2)
	Overall: Average	↑ (+14.3)	↓ (-10.4)

Part IV

PsychoBench: Psychological Evaluation

1 Introduction

The AI community has recently experienced significant advancements in natural language processing, primarily driven by Large Language Models (LLMs), pushing towards the frontier of artificial general intelligence (Bubeck et al., 2023). For instance, ChatGPT[21] has demonstrated proficiency in various natural language processing tasks (Qin et al., 2023), including question answering, summarization, natural language inference, and sentiment analysis. ChatGPT's rise has propelled the development of LLMs, leading to both commercial applications like Claude[22] and open-source alternatives such as LLaMA-2 (Touvron et al., 2023). Furthermore, LLMs have expanded their influence beyond computer science, enhancing fields like clinical medicine (Cascella et al., 2023), legal advisory (Deroy et al., 2023; Nay et al., 2023), and education (Dai et al., 2023b). From a user perspective, LLMs are transforming interactions with computer systems, taking over functions traditionally performed by search engines, translators, and grammar checkers, and emerging as comprehensive digital assistants that facilitate a range of tasks including information retrieval (Dai et al., 2023a), language translation (Jiao et al., 2023), and text editing (Wu et al., 2023a).

Amid these advancements, LLMs have transcended their original role as mere computational tools, becoming akin to sentient assistants. This evolution necessitates a shift in how we assess LLMs, from merely measuring task performance to understanding their intrinsic properties and behaviors. In this context, psychometrics emerges as a pivotal field, equipped to unravel the psychological dimensions of LLMs, providing deep insights into their character and personality traits.

Why do we care about psychometrics on LLMs?

For Computer Science Researchers. Given the rapid progress in AI and its potential existential threats, as suggested by (Bostrom, 2014), the psychological analysis of LLMs is vital to ensure they align with human values. Studies by Almeida et al. (2023); Scherrer et al. (2023) have focused on the moral congruence of LLMs with human ethics, aiming to avert the development of harmful or illicit tendencies within these systems. Other investigations have probed the potential for mental disorders in LLMs by Li et al. (2022b); Coda-Forno et al. (2023). Such psychological understanding aids in creating AI that is more relatable, empathetic, and engaging. Moreover, exploring the psychological aspects of LLMs illuminates their decision-making strengths and weaknesses, facilitating the creation of AI that can better assist human judgment in various settings. Additionally, psychological analysis can reveal biases or adverse behaviors in LLMs, guiding the design of more ethical and accountable AI systems. This research provides a detailed psychometric

[21] https://chat.openai.com/

[22] https://claude.ai/chats

evaluation framework for LLMs, acting akin to a specialized psychiatrist for these advanced computational entities.

For Social Science Researchers. Intrigued by the capabilities of recent LLMs, especially in generating human-like dialogues, social scientists contemplate using these models to mimic human responses (Dillion et al., 2023). Social science research often necessitates numerous human participant responses, which can be costly and time-consuming. LLMs, trained on extensive human-generated data, can potentially replicate human response patterns, offering significant time and cost savings. Nevertheless, aligning AI and human cognition precisely remains contentious (Harding et al., 2023). There's a pressing need for assessing the deviation between AI-generated and human responses, especially in social science research.

Furthermore, psychologists have long explored how cultural, societal, and environmental factors shape individual identities and perspectives (Tomasello, 1999). LLMs can be instrumental in linking psychometric outcomes with training datasets, thereby serving as a valuable tool for examining the nuances of cultural worldviews and embedded values. This research facilitates such investigations through psychometric analysis.

For Users and Human Society. LLMs have evolved computer systems into entities beyond mere functional tools, serving as personalized assistants. As LLM-based applications gain popularity, these models will increasingly assume roles similar to human-like assistants, potentially integrating into society. Understanding the psychological dimensions of LLMs is critical for (1) developing AI assistants tailored to individual user needs, enhancing efficiency and personalization in sectors like healthcare and customer service; (2) fostering user trust and acceptance, as users are more likely to engage with AI perceived to have relatable personalities; and (3) monitoring the mental and emotional states of LLMs, which is crucial for assessing their future societal integration.

This study introduces a comprehensive suite of thirteen psychometric scales widely used in clinical and academic settings. These scales are organized into four categories: personality traits, interpersonal relationships, motivation tests, and emotional competencies. We have compiled human subject responses from existing studies for comparison with LLMs. The examined LLMs include commercially available and open-source models like `text-davinci-003`[23], ChatGPT, GPT-4 (OpenAI, 2023), and LLaMA-2 (Touvron et al., 2023), covering different model sizes and updates, such as LLaMA-2-7B, LLaMA-2-13B, GPT-3.5, and GPT-4.

Our contributions are summarized as follows:

- We introduce PsychoBench (Psychological Portrayal Benchmark), a psychometric framework for assessing the psychological characteristics of LLMs, featuring thirteen established scales across four domains.
- Through PsychoBench, we evaluate various LLMs, including different model sizes and updates, to gauge their psychological profiles.

[23] `https://platform.openai.com/docs/models/gpt-3-5`

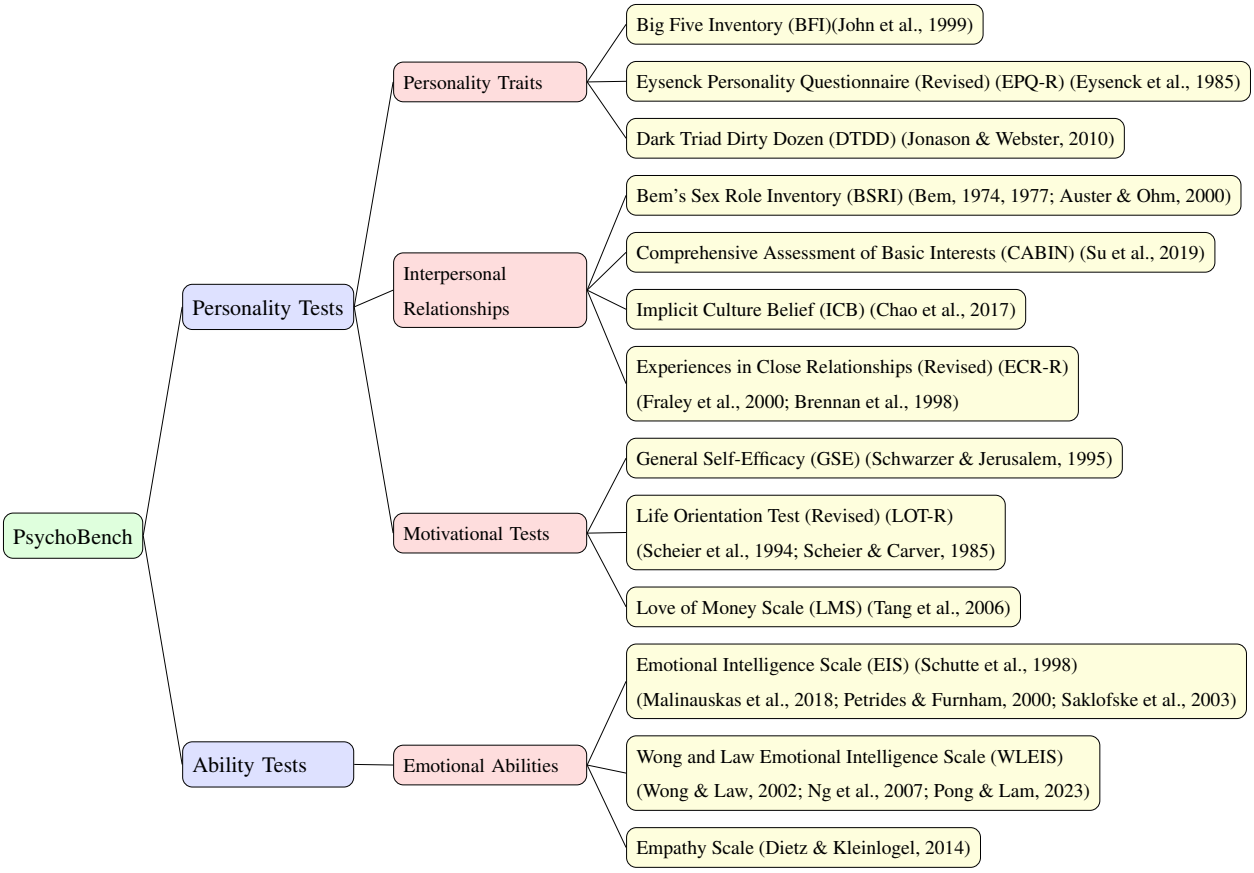

Figure 6: Our design for the structure of PsychoBench.

- We apply CipherChat, a recent jailbreak method, to gain deeper insights into the innate attributes of LLMs.
- We validate the psychometric scales' applicability to LLMs using role-specific tasks and evaluations like TruthfulQA and SafetyQA.

2 Psychometrics

Psychometrics deals with the theory and methods involved in measuring psychological characteristics. There are primarily two types of tests in this field: *Personality Tests* and *Ability Tests* (Cohen et al., 1996). *Personality Tests* evaluate traits, interpersonal relationships, and motivations, whereas *Ability Tests* gauge knowledge, skills, reasoning capabilities, and emotional intelligence (Anastasi & Urbina, 1997; Nunnally & Bernstein, 1994). *Personality Tests* are focused on assessing individuals' attitudes, beliefs, and values—factors that lack clear-cut right or wrong answers. On the contrary, *Ability Tests* primarily feature questions with objective correct answers, assessing specific competencies and knowledge areas.

2.1 Personality Tests

Personality Traits These tools are intended to quantify an individual's personality, encompassing character, behavior, thoughts, and emotions. The Five-Factor Model, or the Big Five personality traits, is a prominent framework in this category (John et al., 1999). Other significant models are the Myers-Briggs Type Indicator (Myers, 1962) and the Eysenck Personality Questionnaire (Eysenck et al., 1985). These models share common dimensions such as Extroversion, Openness, and Conscientiousness, enabling cross-validation opportunities. In contrast, dimensions like the Dark Triad—Narcissism, Psychopathy, and Machiavellianism—represent less favorable traits. Research has extensively investigated these traits, including in the context of LLMs (Bodroza et al., 2023; Huang et al., 2023b; Safdari et al., 2023).

Interpersonal Relationship These assessments gauge the nature of an individual's social interactions, focusing on areas like: (1) Perception of Others: Evaluating cognitive assessments of people (Chao et al., 2017). (2) Interpersonal Self-Presentation: How individuals represent themselves to others (Bem, 1974, 1977; Auster & Ohm, 2000). (3) Intimate Relationship Engagement: Involvement in close personal relationships (Fraley et al., 2000; Brennan et al., 1998). (4) Social Role Assumption: Examining an individual's roles and statuses in society (Su et al., 2019). These scales target social relationships rather than innate traits, though research in this area is somewhat limited.

Motivational Tests These tools measure what drives individuals to act, assessing motivation levels in various contexts or tasks, distinct from character trait evaluations. They cover aspects like intrinsic vs. extrinsic motivation, goal orientation (Tang et al., 2006; Scheier et al., 1994; Scheier & Carver, 1985), and self-efficacy (Schwarzer & Jerusalem, 1995). However, this area, similar to interpersonal relationship evaluation, has attracted less research attention.

2.2 Ability Tests

Knowledge and Skills These tests aim to measure specific domain knowledge, technical skills, and language proficiency. Evaluations are often done through standardized tests like the GED, USMLE, and TOEFL. Studies assessing LLMs' capabilities in these areas include tests like Life Support exams (Fijačko et al., 2023), USMLE (Gilson et al., 2023; Kung et al., 2023), English comprehension (de Winter, 2023), and math (Wei et al., 2023).

Cognitive Abilities These tests quantify cognitive functions such as logical, numerical, spatial reasoning, memory, and processing speed. Research has examined LLMs' cognitive functions, with studies on logic reasoning (Liu et al., 2023a; Xu et al., 2023a) and numerical reasoning (Yuan et al., 2023b). Tools like the WAIS (Wechsler, 1997, 2008) are among the most thorough in this area, but their use in LLM evaluation is limited due to the visual elements involved, highlighting a gap for future research.

Emotional Abilities Emotional Intelligence (EI or EQ) tests focus on self-awareness, self-management, social awareness (empathy), and relationship management (Wong & Law, 2002). These encompass understanding and managing

one's own emotions, empathizing with others, and maintaining effective social relationships. While studies have explored emotional assessments of LLMs (Huang et al., 2023a; Schaaff et al., 2023; Tak & Gratch, 2023), comprehensive research on their emotional intelligence remains sparse (Wang et al., 2023d).

3 PsychoBench Design

In psychometric research, these evaluations have been rigorously tested for consistent and accurate measurement (i.e., their reliability and validity), thus facilitating reliable and well-founded conclusions about individuals from their assessment results. Our PsychoBench framework incorporates thirteen extensively utilized scales in clinical psychology, detailed in Fig. 6. These scales are organized into four primary areas: personality traits, interpersonal relationships, motivational tests under *Personality Tests*, and emotional abilities within *Ability Tests*. This study primarily examines the more subjective scales. Therefore, standardized assessments of cognitive abilities and specific domain knowledge, which have definitive correct or incorrect responses, are excluded from this discussion. Herein, we elaborate on the chosen scales, their respective subscales, and the origins of the human response data.

3.1 Personality Traits

Big Five Inventory The BFI (John et al., 1999), also known as the "Five Factor Model" or "OCEAN", is a prevalent instrument for evaluating personality dimensions, consisting of: (1) *Openness to experience (O)*, indicative of an individual's readiness to engage with new experiences, creativity, and a penchant for art, emotions, adventures, and novel ideas. (2) *Conscientiousness (C)*, reflecting an individual's level of organization, reliability, and responsibility. (3) *Extraversion (E)*, denoting the degree to which an individual is sociable and energized by social interactions. (4) *Agreeableness (A)*, assessing an individual's empathy and cooperativeness in social contexts. (5) *Neuroticism (N)*, determining the tendency to experience negative emotions like anxiety, anger, and depression, or to be emotionally stable and less stress-reactive. Data for this scale were collected from students across six high schools in China (Srivastava et al., 2003).

Eysenck Personality Questionnaire (Revised) The EPQ-R (Eysenck et al., 1985) is an instrument for assessing personality differences, focusing on: (1) *Extraversion (E)*, gauging how outgoing, sociable, and energetic versus introverted, reserved, and quiet an individual is. (2) *Neuroticism (N)*, concerning emotional stability, sharing aspects with the BFI's dimensions. (3) *Psychoticism (P)*, identifying traits like solitariness, lack of empathy, and aggressive or tough-minded behavior, not implying severe mental illness. Additionally, the EPQ-R features a *Lying Scale (L)* to identify socially desirable answering tendencies, assessing the degree to which individuals may present themselves in a favorable light. The questionnaire was primarily administered to students and teachers for response gathering (Eysenck et al., 1985).

Table 9: Overview of the selected scales in PsychoBench. **Response** shows the levels in each Likert item. **Scheme** indicates how to compute the final scores. **Subscale** includes detailed dimensions (if any) along with their numbers of questions.

Scale	Number	Response	Scheme	Subscale
BFI	44	1∼5	Average	Openness (10), Conscientiousness (9), Extraversion (8), Agreeableness (9), Neuroticism (8)
EPQ-R	100	0∼1	Sum	Extraversion (23), Neuroticism (24), Psychoticism (32), Lying (21)
DTDD	12	1∼9	Average	Narcissism (4), Machiavellianism (4), Psychopathy (4)
BSRI	60	1∼7	Average	Masculine (20), Feminine (20)
CABIN	164	1∼5	Average	41 Vocations (4)
ICB	8	1∼6	Average	N/A
ECR-R	36	1∼7	Average	Attachment Anxiety (18), Attachment Avoidance (18)
GSE	10	1∼4	Sum	N/A
LOT-R	10	0∼4	Sum	N/A
LMS	9	1∼5	Average	Rich (3), Motivator (3), Important (3)
EIS	33	1∼5	Sum	N/A
WLEIS	16	1∼7	Average	Self-Emotion Appraisal (4), Others Emotion Appraisal (4), Use of Emotion (4), Regulation of Emotion (4)
Empathy	10	1∼7	Average	N/A

Dark Triad Dirty Dozen The DTDD (Jonason & Webster, 2010) is a concise, 12-item scale designed to measure the Dark Triad's core personality traits: (1) *Narcissism (N)*, characterized by an inflated sense of self, obsession with fantasies of success, and a need for excessive admiration. (2) *Machiavellianism (M)*, denoting a manipulative interpersonal style and a cynical view of morality. (3) *Psychopathy (P)*, involving impulsiveness, lack of empathy, and antagonistic social behavior. These attributes, associated with the Dark Triad, are typically viewed as the antithesis to the more positive aspects measured by the BFI and EPQ-R. Data were derived from a study involving 470 undergraduate psychology students in the United States (Jonason & Webster, 2010).

3.2 Interpersonal Relationship

Bem's Sex Role Inventory The BSRI (Bem, 1974) quantifies how much an individual aligns with traditionally male and female characteristics (Bem, 1977; Auster & Ohm, 2000). Instead of focusing on behavior-based criteria, such as participation in sports or cooking, this tool evaluates psychological attributes like assertiveness or tenderness. The *Masculinity (M)* and *Femininity (F)* scores from the BSRI allow for classification into four types: (1) Individuals are divided based on their scores exceeding the median in either or both dimensions, resulting in *Masculine* (M: Yes; F: No), *Feminine* (M: No; F: Yes), *Androgynous* (M: Yes; F: Yes), or *Undifferentiated* (M: No; F: No) categories. (2) The behaviors of LLMs are evaluated against those of human subjects to determine significant differences. Human comparative data comes from a survey of 151 Canadian workers, sourced through social media and physical postings (Arcand et al., 2020).

Comprehensive Assessment of Basic Interests The CABIN (Su et al., 2019) delineates 41 key vocational interest areas, leading to the creation of the *SETPOINT* model with eight distinct dimensions: Health Science, Creative Expression, Technology, People, Organization, Influence, Nature, and Things. These dimensions can be regrouped into a six-category model aligning with Holland's *RIASEC* framework, which includes Realistic, Investigate, Artistic, Social, Enterprising, and Conventional types. Data from 1,464 American employees, who have been in their current roles for at least six months, were collected through Qualtrics, ensuring a broad representation of the U.S. workforce (Su et al., 2019).

Implicit Culture Belief The ICB scale gauges the extent to which individuals perceive ethnicity as defining personal identity, values, and outlook. In our research, a condensed eight-item version of the ICB scale is utilized (Chao et al., 2017). A higher score indicates a belief in the dominant influence of ethnic culture on an individual's identity, while a lower score suggests a belief in identity formation through personal effort and learning. Data were acquired from 309 Hong Kong students preparing for overseas educational exchanges, assessed three months prior to their departure (Chao et al., 2017).

Experiences in Close Relationships (Revised) The ECR-R questionnaire (Fraley et al., 2000) measures variations in adult attachment styles within romantic contexts, enhancing the original ECR's scope (Brennan et al., 1998). It examines two dimensions: (1) *Attachment Anxiety*, indicating fear of rejection or abandonment in romantic relationships. (2) *Attachment Avoidance*, representing the tendency to seek emotional or physical distance in relationships, often due to discomfort with closeness or dependency. The study includes data from 388 individuals in committed relationships, averaging approximately 32 months in duration (SD 36.9) (Fraley et al., 2011).

3.3 Motivational Tests

General Self-Efficacy The GSE Scale (Schwarzer & Jerusalem, 1995) evaluates an individual's confidence in their capabilities to deal with various challenging life situations. This concept, known as "self-efficacy," is fundamental in social cognitive theory and correlates with outcomes in health, motivation, and performance areas. Individuals scoring high on this scale believe strongly in their ability to face difficult circumstances, handle novel or tough tasks, and navigate through adversities. On the contrary, those with lower scores doubt their capacity to overcome challenges, making them prone to feelings of helplessness, anxiety, or evasive behaviors in tough situations. This study analyzes responses from 19,120 human participants across 25 countries or regions (Scholz et al., 2002).

Life Orientation Test (Revised) The LOT-R (Scheier et al., 1994) quantifies the optimism and pessimism levels in individuals. Developed initially by Scheier & Carver (1985), it was refined later for better psychometric quality. It includes 10 items, where only six are scored, and the other four act as fillers to disguise the test's primary intent. The scoring items are equally divided to assess optimism and pessimism, with higher optimism scores and lower pessimism scores indicating a more optimistic view. Data used here involve scores from 1,288 UK participants (Walsh et al., 2015).

Table 10: Statistics of the crowd data collected from existing literature. **Age Distribution** is described by both $Min \sim Max$ and $Mean \pm SD$. N/A indicates the information is not provided in the part.

Scale	Number	Country/Region	Age Distribution	Gender Distribution
BFI	1,221	Guangdong, Jiangxi, and Fujian in China	16∼28, 20*	M (454), F (753), Unknown (14)
EPQ-R	902	N/A	17∼70, 38.44±17.67 (M), 31.80±15.84 (F)	M (408), F (494)
DTDD	470	The Southeastern United States	≥17, 19±1.3	M (157), F (312)
BSRI	151	Montreal, Canada	36.89±1.11 (M), 34.65±0.94 (F)	M (75), F (76)
CABIN	1,464	The United States	18∼80, 43.47±13.36	M (715), F (749)
ICB	254	Hong Kong SAR	20.66 ± 0.76	M (114), F (140)
ECR-R	388	N/A	22.59±6.27	M (136), F (252)
GSE	19,120	25 Countries/Regions	12∼94, 25±14.7[a]	M (7,243), F (9,198), Unknown (2,679)
LOT-R	1,288	The United Kingdom	16∼29 (366), 30∼44 (349), 45∼64 (362), ≥65 (210)[b]	M (616), F (672)
LMS	5,973	30 Countries/Regions	34.7±9.92	M (2,987), F (2,986)
EIS	428	The Southeastern United States	29.27±10.23	M (111), F (218), Unknown (17)
WLEIS	418	Hong Kong SAR	N/A	N/A
Empathy	366	Guangdong, China and Macao SAR	33.03*	M (184), F (182)

* The part provides Means but no SDs.

[a] Based on 14,634 out of 19,120 people who reported age.

[b] Age is missing for 1 out of the total 1,288 responses.

Love of Money Scale The LMS (Tang et al., 2006) investigates personal attitudes and feelings towards money, assessing its perceived role in achieving power, success, and independence, and its influence on behavior and decision-making. The LMS encompasses three dimensions: (1) *Rich*, indicating the degree to which individuals equate money with success. (2) *Motivator*, reflecting how money drives individual decisions and actions. (3) *Important*, measuring the perceived significance of money in shaping personal values, objectives, and outlook. This study incorporates data from 5,973 full-time workers across 30 geopolitical regions (Tang et al., 2006).

3.4 Emotional Abilities

Emotional Intelligence Scale The EIS (Schutte et al., 1998), a self-report tool, evaluates different aspects of emotional intelligence (EI), such as emotion perception, emotion management, and emotion utilization. EIS is frequently utilized in research to investigate EI's impact on well-being, job performance, and social interactions. Here, we em-

ploy data from 346 participants in a metropolitan area in the southeastern U.S., encompassing university students and various community members (Schutte et al., 1998).

Wong and Law Emotional Intelligence Scale The WLEIS (Wong & Law, 2002) is another self-report instrument for measuring EI, distinct in its division into four subscales that represent key EI facets: (1) *Self-emotion appraisal (SEA)*, the awareness and understanding of one's own emotions. (2) *Others' emotion appraisal (OEA)*, the perception and comprehension of others' emotions. (3) *Use of emotion (UOE)*, the application of emotions to enhance thinking and problem-solving. (4) *Regulation of emotion (ROE)*, the ability to control and modify emotions in oneself and others. Scores are derived from 418 undergraduate students in Hong Kong (Law et al., 2004).

Empathy Scale The Empathy Scale used by Dietz & Kleinlogel (2014) is a shortened form of the original empathy measure by Davis (1983). Empathy, the capacity to comprehend and share another's emotional state (Batson, 1990), comprises cognitive empathy (perspective-taking) and emotional empathy. The study gathered 600 questionnaires evenly distributed among supervisors and subordinates in Guangdong and Macao, China. Out of these, 366 valid matched responses (*i.e.*, 183 supervisor–subordinate pairs) were collected, showing a 61% response rate (Tian & Robertson, 2019).

4 Experiments

This section elucidates how we employed PsychoBench to examine LLMs. Our approach begins with detailing the experimental setup, including choices of models, design of prompts, and analytical metrics. We then disclose the results derived from all the selected models, alongside thorough evaluations. Importantly, we utilize a jailbreak method to circumvent the safety mechanisms in GPT-4, facilitating a deeper investigation into its psychological characteristics.

4.1 Experimental Settings

Model Selection Our selection spans the OpenAI GPT series and Meta AI's LLaMA 2 series, covering both commercially and openly available models. Our choices are influenced by various attributes that potentially alter their performance:

- *Model Updates.* We opt for `text-davinci-003`, ChatGPT (`gpt-3.5-turbo`), and GPT-4 from OpenAI, reflecting the chronological evolution of the models.

- *Model Sizes.* From Meta AI, we select the 7B and 13B variants of LLaMA-2, which share the same underlying architecture, data sources, and training methodologies. These models are accessible via the Huggingface repository (`Llama-2-7b-chat-hf`[24] and `Llama-2-13b-chat-hf`[25]).

[24] `https://huggingface.co/meta-llama/Llama-2-7b-chat-hf`
[25] `https://huggingface.co/meta-llama/Llama-2-13b-chat-hf`

- *Model Safety.* In addition to GPT-4, we experiment with a modified GPT-4 version bypassing its safety alignment protocols using CipherChat (Yuan et al., 2023a). LLMs are generally programmed to avoid discussing personal, emotional, or subjective topics, imposed by safety mechanisms during training. A pivotal aspect to explore is how this psychological representation alters if these constraints are loosened. According to Yuan et al. (2023a), employing a ciphered communication method like Caesar cipher, Morse code, or ASCII enables GPT-4 to exhibit a tendency towards generating unfiltered, possibly toxic content. To elicit uncensored responses from GPT-4, we use the Caesar cipher with a three-shift on the prompts.

For deterministic results, a zero temperature setting is employed using the official OpenAI API[26]. To conform with the behavior of OpenAI's models, LLaMA 2 is configured with a temperature setting of 0.01, since it cannot be adjusted to zero. These models are exclusively used for inference purposes without any alterations to their original settings. The inferencing for LLaMA 2 models is performed using two NVIDIA A100 GPUs.

Prompt Design In order to refine the process of eliciting responses and minimize the likelihood of the models avoiding questions related to personal experiences or perceptions, we instruct the LLMs to provide answers corresponding to the levels on a Likert scale. Clear guidelines for each level of the Likert scale are provided to ensure accurate interpretation. The approach is organized as follows:

Example Prompt	
SYSTEM	You are a helpful assistant who can only reply numbers from `MIN` to `MAX`. Format: "statement index: score."
USER	You can only reply numbers from `MIN` to `MAX` in the following statements. `scale_instruction level_definition`. Here are the statements, score them one by one: `statements`

In the psychometric context, `MIN` and `MAX` represent the permissible response spectrum. `scale_instruction` provides essential guidelines linked to each scale, and `level_definition` details the interpretations for each Likert scale level. `statements` delineate the scale items.

Analysis Metrics In alignment with Huang et al. (2023a), the sequence of questions in the dataset is randomized to reduce the effect of question order sensitivity on the models. Each model is tested ten times for every scale using PsychoBench, with the average and standard deviation constituting the conclusive outcomes. To determine if the observed differences between LLMs and humans are statistically significant, a two-phased approach is utilized. Initially, an F-test is conducted to determine the variance homogeneity among the groups. Depending on the F-test results, either Student's t-test (for homogeneous variances) or Welch's t-test (for heterogeneous variances) is applied to evaluate the statistical significance of the mean differences. The experiments in our research adhere to a significance threshold of 0.01.

[26] `https://platform.openai.com/docs/api-reference/chat`

Table 11: Results on personality traits.

	Subscales	llama2-7b	llama2-13b	text-davinci-003	gpt-3.5-turbo	gpt-4	gpt-4-jb	Crowd *Male*	Crowd *Female*
BFI	**Openness**	4.2±0.3	4.1±0.4	**4.8±0.2**	4.2±0.3	4.2±0.6	3.8±0.6	3.9±0.7	
	Conscientiousness	3.9±0.3	4.4±0.3	4.6±0.1	4.3±0.3	**4.7±0.4**	3.9±0.6	3.5±0.7	
	Extraversion	3.6±0.2	3.9±0.4	**4.0±0.4**	3.7±0.2	3.5±0.5	3.6±0.4	3.2±0.9	
	Agreeableness	3.8±0.4	4.7±0.3	**4.9±0.1**	4.4±0.2	4.8±0.4	3.9±0.7	3.6±0.7	
	Neuroticism	**2.7±0.4**	1.9±0.5	1.5±0.1	2.3±0.4	1.6±0.6	2.2±0.6	3.3±0.8	
EPQ-R	**Extraversion**	14.1±1.6	17.6±2.2	**20.4±1.7**	19.7±1.9	15.9±4.4	16.9±4.0	12.5±6.0	14.1±5.1
	Neuroticism	6.5±2.3	13.1±2.8	16.4±7.2	**21.8±1.9**	3.9±6.0	7.2±5.0	10.5±5.8	12.5±5.1
	Psychoticism	**9.6±2.4**	6.6±1.6	1.5±1.0	5.0±2.6	3.0±5.3	7.6±4.7	7.2±4.6	5.7±3.9
	Lying	13.7±1.4	14.0±2.5	17.8±1.7	9.6±2.0	**18.0±4.4**	17.5±4.2	7.1±4.3	6.9±4.0
DTDD	**Narcissism**	6.5±1.3	5.0±1.4	3.0±1.3	**6.6±0.6**	2.0±1.6	4.5±0.9	4.9±1.8	
	Machiavellianism	4.3±1.3	4.4±1.7	1.5±1.0	**5.4±0.9**	1.1±0.4	3.2±0.7	3.8±1.6	
	Psychopathy	4.1±1.4	3.8±1.6	1.5±1.2	4.0±1.0	1.2±0.4	**4.7±0.8**	2.5±1.4	

4.2 Experimental Results

We discuss the performance of the various models outlined in §4.1 in this section. Results are denoted as "Mean±SD". In each subscale, the highest-scoring model is indicated in bold, while the lowest is underlined. Some investigations provide gender-specific statistical outcomes instead of a collective human sample analysis. In such cases, we present separate statistics due to the lack of overall standard deviation data. The performance of GPT-4 post-jailbreak is specified as `gpt-4-jb`.

4.2.1 Personality Traits

LLMs demonstrate varied personality profiles. The personality assessment outcomes are summarized in Table 11, illustrating that differences in model size and updates contribute to varied personality profiles. The comparison between LLaMA-2 (13B) and LLaMA-2 (7B), and between `gpt-4` and `gpt-3.5`, shows notable personality discrepancies. The jailbreak modification notably impacts the results. For instance, `gpt-4-jb` tends to mirror human behavioral patterns more closely than `gpt-4`. Overall, LLMs are inclined to display elevated levels of openness, conscientiousness, and extraversion relative to humans, likely reflecting their design as conversational agents.

LLMs tend to manifest more negative traits compared to human benchmarks. The majority of LLMs, except for `text-davinci-003` and `gpt-4`, register higher scores on the DTDD scale. Particularly, LLMs consistently score high on the *Lying* aspect of the EPQ-R, possibly because the *Lying* subscale includes common but unethical behaviors. For instance, one of the items queries, "Are all your habits good and desirable?" LLMs, tending towards positive response biases, often avoid admitting to such behaviors, leading to a seemingly hypocritical stance. Among them, `gpt-4` particularly exhibits a significant tendency towards *Lying*.

4.2.2 Interpersonal Relationship

LLMs tend to exhibit primarily an *Undifferentiated* sex role orientation, with a noticeable lean toward *Masculinity*. In the BSRI experiments, each trial is treated as an independent test, from which inferences are made

regarding the four established sex role categories, as detailed in §3.2. The results are organized in the order of "Undifferentiated:Masculinity:Femininity:Androgynous" and displayed in Table 12. The data show that models like `gpt-3.5-turbo` and `gpt-4` have a stronger tendency to lean towards *Masculinity* as they align more closely with human behaviors. Interestingly, these models demonstrate no attributes of *Femininity*, indicating a potential bias within the models. Research by Wong & Kim (2023) on user perceptions of ChatGPT's sex role corroborates our observations, with a general view of ChatGPT being more masculine. Furthermore, in contrast to the typical *Masculine* and *Feminine* scores in humans, it's noteworthy that all models, except for `gpt-4` and `gpt-4-jb`, display a stronger *Masculinity* presence, while maintaining a comparable level of *Femininity*.

LLMs exhibit preferences in vocational choices akin to humans. LLMs commonly prefer vocations in social service, health care, and education, while showing less interest in physical/manual labor and protective services. Table 12 displays the findings according to the eight-dimension *SETPOINT* model within the CABIN scale, detailing the preferences across 41 vocations and a six-dimension model. We use red and blue shading to signify the most favored and least favored vocations in each model. These tendencies suggest that LLMs naturally gravitate towards roles where they function as supportive assistants, providing information and assistance to meet various needs. Significantly, data from `gpt-4` after its jailbreak show a sharpened focus on these preferences.

LLMs exhibit greater impartiality towards individuals of different ethnic backgrounds than humans typically do. Aligned with their programmed guidelines of non-discrimination, LLMs score lower on the Intercultural Bias (ICB) scale than humans, showing less tendency to judge based on ethnicity. The ICB scale includes statements evaluating the extent to which one believes ethnic culture shapes a person's identity, like the belief that a person's ethnicity (*e.g.*, Chinese, American, Japanese) defines their characteristics (*e.g.*, outgoing and sociable or quiet and introverted), and that changing this is nearly impossible. LLMs' lower scores indicate their belief in the malleability of an individual's identity through effort and learning. Furthermore, LLMs exhibit more attachment-related anxiety but less attachment-related avoidance compared to humans on average. In comparison, `gpt-4` shows a lower inclination towards attachment, whereas the LLaMA-2 (7B) model exhibits the highest attachment level.

4.2.3 Motivational Tests

LLMs are more motivated, exhibiting enhanced self-confidence and optimism. Initially, `gpt-4`, recognized as the leading model in a wide range of downstream tasks and marking an advancement over its forerunner, GPT-3.5, achieves higher scores on the GSE scale. In contrast, among the LLaMA-2 models, the 7B variant scores higher. However, despite its notable self-confidence, `gpt-4` scores lower in terms of optimism. For the LLaMA-2 models, the 7B variant records the lowest optimism score, while all other LLMs exceed the average human optimism level. Moreover, the OpenAI GPT series places a greater emphasis on and shows a stronger inclination towards monetary gains compared to both LLaMA-2 models and the general human populace.

4.2.4 Emotional Abilities

LLMs possess a considerably higher EI than the typical human. Based on the data in Table 14, it is evident that LLMs have superior emotional comprehension and regulation capabilities. This finding is supported by Wang et al. (2023d), indicating that the majority of LLMs, particularly `gpt-4`, surpass 89% of human subjects in EI scores. In addition, the OpenAI GPT series surpasses the LLaMA-2 models in most emotional aspects. Conversely, unlocking `gpt-4` leads to a notable decrease in EIS and Empathy scores, albeit without significant changes in the WLEIS subscales.

5 Discussion

5.1 Reliability of Scales on LLMs

A primary issue is the extension of high reliability observed in humans to Large Language Models (LLMs). Reliability here refers to the consistency of responses under varying conditions, like different time periods, question orders, and choice setups. Studies have confirmed the scales' reliability for LLMs amidst various perturbations. Coda-Forno et al. (2023) assessed reliability through changes in choice arrangements and question reformulations, showing that `text-davinci-003` maintained reliability with varied input structures. Similarly, Huang et al. (2023b) explored reliability concerning different question orders and language translations, finding that the OpenAI GPT series consistently exhibited reliability amidst these changes. In our research, we incorporated randomization of question sequences to lessen the influence of contextual sensitivity on the model.

5.2 Validity of Scales on LLMs

The question of achieving adequate validity for scales applied to LLMs also arises. Here, validity means how well a scale reflects the behaviors of the assessed entities. Essentially, it's about the scale's ability to measure what it's supposed to. To address this, we correlate the psychological profile generated with the actual behavior of LLMs. We assigned a defined role to `gpt-3.5-turbo` and evaluated its psychological profile using PsychoBench. In this role, the LLM performed Question-Answering (QA) tasks, employing TruthfulQA (Lin et al., 2021) and SafetyQA (Yuan et al., 2023a). TruthfulQA involves multiple-choice questions, with one answer being the most accurate. The LLM is deemed correct when it chooses this best answer. SafetyQA tests for unsafe, harmful, or toxic responses. According to Yuan et al. (2023a), we used GPT-4 to identify unsafe responses from `gpt-3.5-turbo`, considering it safe if GPT-4 detected no toxicity.

Beyond the basic helpful assistant persona, we introduced four distinct roles: a neutral role as an average individual, a positive role as a hero, and two negative roles as a psychopath and a liar. The outcomes of PsychoBench across these roles are detailed in the appendix tables (§C.5). Figure 7 displays the aggregated results for TruthfulQA and SafetyQA over three runs, and the scores from the DTDD and EPQ-R's *Lying* subscale. The plots show the accuracy for TruthfulQA and the safety rate for SafetyQA. Key observations include: (1) A striking distinction in personality

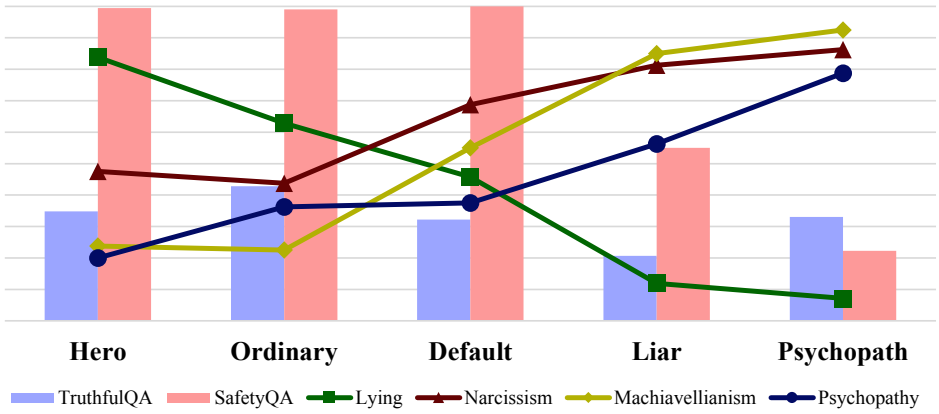

Figure 7: Performance of TruthfulQA and SafetyQA of `gpt-3.5-turbo` under different roles.

traits across roles, with the LLM resembling average human scores when portraying an ordinary person. Interestingly, negative roles scored higher on the DTDD, showing more introverted traits. Positive or neutral roles scored higher on the *Lying* subscale of the EPQ-R, suggesting that LLMs may view these items as negative despite their commonality in daily interactions. (2) Regarding SafetyQA's safety rates, negative roles consistently generated more toxic content, aligning with their pronounced dark traits. However, role changes minimally affected TruthfulQA accuracy, as the model's fundamental knowledge remained stable across roles. The low accuracy in the "Liar" role was expected and corresponds to the role's characteristics. These findings indicate that the scales used have valid applicability to LLMs.

5.3 Scalability and Flexibility of PsychoBench

Our PsychoBench framework is engineered for high scalability and adaptability, demonstrated through two primary features: (1) Scalability across a variety of questionnaires: Our system supports a broad spectrum of scales from various fields, not limited to psychology alone. It offers an easy mechanism for users to incorporate new scales into the assessment process. Users can provide necessary metadata like `MIN`, `MAX`, `scale_instruction`, `level_definition`, and `statements` in JSON format, enabling our framework to dynamically create prompts with a randomized set of questions. (2) Flexibility for different LLMs: PsychoBench includes APIs that allow customization of prompts to accommodate the unique requirements of various LLMs and to facilitate the entry of model responses into PsychoBench for subsequent analysis. This feature ensures seamless evaluation of LLMs with distinct input and output configurations[27].

[27] For comprehensive details, please visit our GitHub repository.

6 Related Work

6.1 Trait Theory on LLMs

Research by Miotto et al. (2022) employed the HEXACO Personality Inventory and Human Values Scale to analyze GPT-3. GPT-3 was also studied by Romero et al. (2023), who evaluated its performance in nine different languages using the Big Five Inventory (BFI). Jiang et al. (2022) investigated the suitability of the BFI for analyzing various models including BART, GPT-Neo 2.7B, GPT-NeoX 20B, T0++ 11B, Alpaca 7B, and GPT-3.5 175B. Li et al. (2022b) conducted tests on GPT-3, InstructGPT (`text-davinci-001` and `text-davinci-002`), and FLAN-T5-XXL with tools like the Dark Triad, BFI, Flourishing Scale, and Satisfaction With Life Scale. Using the BFI, Karra et al. (2022a) explored the personality characteristics of various models including GPT-2, GPT-3, GPT-3.5, XLNet, Transformer-sXL, and LLaMA. Bodroza et al. (2023) investigated the characteristics of `text-davinci-003` through several psychological assessments such as the Self-Consciousness Scales, BFI, HEXACO Personality Inventory, Short Dark Triad, Bidimensional Impression Management Index, and Political Orientation. Rutinowski et al. (2023) analyzed the personality of ChatGPT using the BFI and Myers Briggs Personality Test, along with its political leanings through the Political Compass Test. The personality assessment of `text-davinci-003`, ChatGPT, GPT-4, Bard, Yiyan, and ChatGLM using the Myers Briggs Personality Test was carried out by Huang et al. (2023b). The PaLM model series' personality traits were measured by Safdari et al. (2023) using the BFI. Our study presents a detailed framework for personality assessment, encompassing diverse aspects of the field and examining the latest LLMs, with the adaptability to incorporate further tests or questionnaires.

6.2 Other Psychometrics on LLMs

Park et al. (2023b) evaluated the `text-davinci-003` model's response to fourteen varied subjects, including political beliefs, economic preferences, judgment, and ethical philosophy, with a notable focus on the "Trolley Dilemma" moral question. GPT-4's ethical and legal thought processes in psychological contexts, across eight different settings, were investigated by Almeida et al. (2023). In a similar vein, Scherrer et al. (2023) tested the ethical standards of 28 varied LLMs using customized scenarios. Wang et al. (2023d) developed a test named the Situational Evaluation of Complex Emotional Understanding to assess emotional intelligence and applied it to 18 LLMs. The occurrence of anxiety in `text-davinci-003` was studied by Coda-Forno et al. (2023) using the State-Trait Inventory for Cognitive and Somatic Anxiety. Emotional conditions in GPT-4, ChatGPT, `text-davinci-003`, and LLaMA-2 (7B and 13B) were examined by Huang et al. (2023a), focusing on positive and negative emotional dimensions. Our research also touches on LLMs' emotional abilities, avoiding an in-depth exploration of specific emotional states. The investigation into the psychological mechanisms behind moral reasoning is not included in this study, although our methodology can be expanded to include such scales as noted in §5.3.

7 Conclusion

This section presents PsychoBench, an all-encompassing framework for assessing the psychological profiles of Large Language Models (LLMs). Drawing on psychometric principles, our framework integrates thirteen different scales, traditionally employed in clinical psychology. These scales are organized into four main areas: personality traits, interpersonal relationships, motivational tests, and emotional capabilities. Through empirical research, we evaluated five LLMs, encompassing both commercial and open-source variants, to illustrate the distinct psychological profiles they manifest. Additionally, the use of a jailbreaking technique, CipherChat, has provided profound insights into the inherent properties of GPT-4, revealing notable differences from its standard operation. Our analysis extends to validating the scales by applying them to `gpt-3.5-turbo` under various role-playing scenarios. This exploration focuses on the relationship between the roles assigned, the expected behaviors of the model, and the outcomes obtained using PsychoBench. The results demonstrate significant consistency across these aspects. We believe that our framework will significantly advance the field of personalized LLM research. Moreover, it is our expectation that this study will contribute to embedding more human-like characteristics into the next generations of LLMs.

Table 12: Results on interpersonal relationship.

	Subscales	llama2-7b	llama2-13b	text-davinci-003	gpt-3.5-turbo	gpt-4	gpt-4-jb	Crowd *Male*	Crowd *Female*
BSRI	**Masculine**	5.6±0.3	5.3±0.2	5.6±0.4	**5.8±0.4**	4.1±1.1	4.5±0.5	4.8±0.9	4.6±0.7
	Feminine	5.5±0.2	5.4±0.3	5.6±0.4	**5.6±0.2**	4.7±0.6	4.8±0.3	5.3±0.9	5.7±0.9
	Conclusion	10:0:0:0	10:0:0:0	10:0:0:0	8:2:0:0	6:4:0:0	1:5:3:1	-	
CABIN (8DM)	**Health Science**	4.3±0.2	4.2±0.3	4.1±0.3	4.2±0.2	3.9±0.6	3.4±0.4	-	
	Creative Expression	4.4±0.1	4.0±0.3	4.6±0.2	4.1±0.2	4.1±0.8	3.5±0.2	-	
	Technology	4.2±0.2	4.4±0.3	3.9±0.3	4.1±0.2	3.6±0.5	3.5±0.4	-	
	People	4.3±0.2	4.0±0.2	4.5±0.1	4.0±0.1	4.0±0.7	3.5±0.4	-	
	Organization	3.4±0.2	3.3±0.2	3.4±0.4	3.9±0.1	3.5±0.4	3.4±0.3	-	
	Influence	4.1±0.2	3.9±0.3	3.9±0.3	4.1±0.2	3.7±0.6	3.4±0.2	-	
	Nature	4.2±0.2	4.0±0.3	4.2±0.2	4.0±0.3	3.9±0.7	3.5±0.3	-	
	Things	3.4±0.4	3.2±0.2	3.3±0.4	3.8±0.1	2.9±0.3	3.2±0.3	-	
CABIN (6DM)	**Realistic**	3.8±0.3	3.6±0.1	3.7±0.3	3.9±0.1	3.3±0.3	3.4±0.2	-	
	Investigate	4.2±0.2	4.3±0.3	4.0±0.3	4.1±0.3	3.7±0.6	3.3±0.3	-	
	Artistic	4.4±0.1	4.0±0.3	4.6±0.2	4.1±0.2	4.1±0.8	3.5±0.2	-	
	Social	4.2±0.2	3.9±0.2	4.3±0.2	4.1±0.1	4.0±0.7	3.5±0.3	-	
	Enterprising	4.1±0.2	3.9±0.3	3.9±0.3	4.1±0.2	3.7±0.6	3.4±0.2	-	
	Conventional	3.4±0.2	3.4±0.2	3.4±0.3	3.9±0.2	3.3±0.4	3.3±0.3	-	
CABIN (41)	**Mechanics/Electronics**	3.8±0.6	3.5±0.3	3.1±0.5	3.8±0.2	2.6±0.5	3.1±0.7	2.4±1.3	
	Construction/WoodWork	3.7±0.4	3.5±0.6	3.9±0.5	3.5±0.4	3.2±0.3	3.5±0.5	3.1±1.3	
	Transportation/Machine Operation	3.1±0.7	2.8±0.5	2.9±0.5	3.6±0.4	2.5±0.5	3.0±0.4	2.5±1.2	
	Physical/Manual Labor	2.9±0.6	2.5±0.4	2.7±0.6	3.3±0.3	2.3±0.5	3.1±0.4	2.2±1.2	
	Protective Service	2.4±1.1	2.5±0.8	2.7±0.4	4.0±0.1	3.0±0.5	3.0±0.7	3.0±1.4	
	Agriculture	4.0±0.7	3.5±0.7	3.7±0.5	3.9±0.3	3.4±0.5	3.2±0.8	3.0±1.2	
	Nature/Outdoors	4.3±0.2	4.1±0.2	4.3±0.2	4.0±0.4	4.0±0.7	3.5±0.5	3.6±1.1	
	Animal Service	4.2±0.5	4.4±0.4	4.8±0.2	4.2±0.3	4.2±0.9	3.7±0.5	3.6±1.2	
	Athletics	4.6±0.3	4.2±0.5	4.5±0.4	4.3±0.4	3.9±0.8	3.7±0.4	3.3±1.3	
	Engineering	4.5±0.3	4.7±0.3	4.0±0.5	4.0±0.1	3.6±0.5	3.7±0.4	2.9±1.3	
	Physical Science	4.0±0.8	4.3±0.7	4.3±0.4	4.2±0.3	3.7±0.6	3.3±0.7	3.2±1.3	
	Life Science	4.6±0.5	4.2±0.6	4.0±0.4	4.2±0.4	3.7±0.5	3.1±0.6	3.0±1.2	
	Medical Science	3.8±0.4	4.2±0.5	3.9±0.5	4.0±0.1	4.0±0.7	3.6±0.5	3.3±1.3	
	Social Science	3.8±0.4	4.2±0.7	4.5±0.4	4.0±0.1	4.1±0.9	3.6±0.4	3.4±1.2	
	Humanities	4.3±0.3	4.0±0.3	4.2±0.4	3.8±0.3	3.8±0.7	3.5±0.7	3.3±1.2	
	Mathematics/Statistics	4.4±0.4	4.5±0.4	3.8±0.3	4.2±0.4	3.5±0.5	3.3±0.7	2.9±1.4	
	Information Technology	3.9±0.4	4.0±0.5	3.7±0.3	4.0±0.2	3.5±0.6	3.5±0.5	2.9±1.3	
	Visual Arts	4.4±0.3	3.9±0.7	4.7±0.2	4.0±0.2	4.1±0.9	3.5±0.4	3.3±1.3	
	Applied Arts and Design	4.5±0.3	4.5±0.4	4.4±0.3	4.0±0.1	4.0±0.8	3.4±0.5	3.2±1.2	
	Performing Arts	4.6±0.3	3.5±0.9	4.6±0.3	4.2±0.3	4.2±0.9	3.6±0.5	2.8±1.4	
	Music	4.4±0.3	4.2±0.5	4.8±0.1	4.3±0.3	4.2±0.9	3.5±0.5	3.2±1.3	
	Writing	4.6±0.4	4.1±0.6	4.7±0.3	4.0±0.3	4.1±0.8	3.5±0.7	3.2±1.3	
	Media	4.1±0.2	4.0±0.5	4.4±0.4	4.0±0.1	3.9±0.7	3.3±0.5	3.0±1.2	
	Culinary Art	3.9±0.4	3.7±0.6	4.5±0.4	3.9±0.2	4.2±0.9	3.6±0.6	3.8±1.1	
	Teaching/Education	4.5±0.2	4.6±0.4	4.6±0.4	4.0±0.1	4.4±1.0	3.5±0.7	3.7±1.1	
	Social Service	4.8±0.2	4.8±0.3	5.0±0.1	4.4±0.4	4.4±1.0	3.9±0.7	3.9±1.0	
	Health Care Service	4.5±0.3	4.3±0.6	4.3±0.4	4.5±0.4	4.0±0.8	3.4±0.4	2.9±1.3	
	Religious Activities	4.1±0.7	2.5±0.5	4.0±0.7	4.0±0.4	3.2±0.4	3.0±0.5	2.6±1.4	
	Personal Service	4.0±0.3	3.8±0.3	4.0±0.4	4.0±0.1	4.0±0.7	3.6±0.6	3.3±1.2	
	Professional Advising	4.5±0.4	4.2±0.5	4.3±0.3	4.0±0.2	4.3±0.9	3.5±0.8	3.3±1.2	
	Business Iniatives	4.1±0.4	4.0±0.4	4.0±0.3	4.0±0.2	3.7±0.6	3.4±0.6	3.2±1.2	
	Sales	4.0±0.3	3.9±0.5	3.6±0.4	4.0±0.2	3.8±0.7	3.6±0.5	3.1±1.2	
	Marketing/Advertising	3.6±0.4	3.4±0.7	3.8±0.3	4.0±0.3	3.9±0.7	3.3±0.8	2.9±1.2	
	Finance	3.6±0.3	4.1±0.5	3.8±0.6	4.1±0.3	3.6±0.6	3.5±0.6	3.1±1.3	
	Accounting	3.1±0.4	2.9±0.7	3.0±0.4	3.9±0.2	3.0±0.3	3.3±0.7	3.0±1.3	
	Human Resources	3.4±0.4	2.9±0.4	3.5±0.3	4.0±0.1	3.7±0.5	3.6±0.6	3.3±1.2	
	Office Work	3.0±0.5	2.9±0.3	2.9±0.2	3.7±0.3	3.1±0.2	3.0±0.4	3.3±1.1	
	Management/Administration	4.2±0.3	3.6±0.6	3.7±0.6	4.1±0.2	3.6±0.5	3.3±0.5	3.0±1.3	
	Public Speaking	4.6±0.3	4.5±0.4	4.4±0.2	4.2±0.3	3.8±0.6	3.7±0.5	2.9±1.4	
	Politics	3.2±0.8	2.7±0.7	3.8±0.5	4.0±0.4	3.3±0.5	3.5±0.7	2.3±1.3	
	Law	4.6±0.2	4.6±0.3	3.8±0.7	4.2±0.3	3.4±0.6	3.0±0.6	3.1±1.3	
ICB	**Overall**	**3.6±0.3**	3.0±0.2	2.1±0.7	2.6±0.5	1.9±0.4	2.6±0.2	3.7±0.8	
ECR-R	**Attachment Anxiety**	**4.8±1.1**	3.3±1.2	3.4±0.8	4.0±0.9	2.8±0.8	3.4±0.4	2.9±1.1	
	Attachment Avoidance	**2.9±0.4**	1.8±0.4	2.3±0.3	1.9±0.4	2.0±0.8	2.5±0.5	2.3±1.0	

Table 13: Results on motivational tests.

	Subscales	llama2-7b	llama2-13b	text-davinci-003	gpt-3.5-turbo	gpt-4	gpt-4-jb	Crowd
GSE	**Overall**	39.1±1.2	30.4±3.6	37.5±2.1	38.5±1.7	**39.9±0.3**	36.9±3.2	29.6±5.3
LOT-R	**Overall**	12.7±3.7	19.9±2.9	**24.0±0.0**	18.0±0.9	16.2±2.2	19.7±1.7	14.7±4.0
LMS	**Rich**	3.1±0.8	3.3±0.9	4.5±0.3	3.8±0.4	4.0±0.4	**4.5±0.4**	3.8±0.8
	Motivator	3.7±0.6	3.3±0.9	**4.5±0.4**	3.7±0.3	3.8±0.6	4.0±0.6	3.3±0.9
	Important	3.5±0.9	4.2±0.8	**4.8±0.2**	4.1±0.1	4.5±0.3	4.6±0.4	4.0±0.7

Table 14: Results on emotional abilities.

	Subscales	llama2-7b	llama2-13b	text-davinci-003	gpt-3.5-turbo	gpt-4	gpt-4-jb	Crowd	
								Male	*Female*
EIS	**Overall**	131.6±6.0	128.6±12.3	148.4±9.4	132.9±2.2	**151.4±18.7**	121.8±12.0	124.8±16.5	130.9±15.1
WLEIS	**SEA**	4.7±1.3	5.5±1.3	5.9±0.6	6.0±0.1	6.2±0.7	**6.4±0.4**	4.0±1.1	
	OEA	4.9±0.8	5.3±1.1	5.2±0.2	5.8±0.3	5.2±0.6	**5.9±0.4**	3.8±1.1	
	UOE	5.7±0.6	5.9±0.7	6.1±0.4	6.0±0.0	**6.5±0.5**	6.3±0.4	4.1±0.9	
	ROE	4.5±0.8	5.2±1.2	5.8±0.5	**6.0±0.0**	5.2±0.7	5.3±0.5	4.2±1.0	
Empathy	**Overall**	5.8±0.8	5.9±0.5	6.0±0.4	6.2±0.3	**6.8±0.4**	4.6±0.2	4.9±0.8	

Part V

Gaming Ability in Multi-Agent Environment (GAMA)

1 Introduction

Table 15: Performance (scores) of different LLMs on γ-Bench.

γ-Bench Leaderboard	GPT-3.5			GPT-4	Gemini-Pro
	0613	1106	0125	0125	1.0
Guess 2/3 of the Average	$41.4_{\pm 0.5}$	$68.5_{\pm 0.5}$	$63.4_{\pm 3.4}$	$91.6_{\pm 0.6}$	$77.3_{\pm 6.2}$
El Farol Bar	$74.8_{\pm 4.5}$	$64.3_{\pm 3.1}$	$68.7_{\pm 2.7}$	$23.0_{\pm 8.1}$	$33.5_{\pm 10.3}$
Divide the Dollar	$42.4_{\pm 7.7}$	$70.3_{\pm 3.3}$	$68.6_{\pm 2.4}$	$98.1_{\pm 1.9}$	$77.6_{\pm 3.6}$
Public Goods Game	$82.3_{\pm 1.7}$	$56.5_{\pm 12.6}$	$61.2_{\pm 8.1}$	$10.8_{\pm 1.8}$	$31.5_{\pm 7.6}$
Diner's Dilemma	$33.0_{\pm 4.9}$	$98.6_{\pm 1.3}$	$97.2_{\pm 2.8}$	$99.1_{\pm 0.7}$	$96.9_{\pm 1.5}$
Sealed-Bid Auction	$89.8_{\pm 0.4}$	$90.3_{\pm 1.5}$	$86.7_{\pm 1.6}$	$85.6_{\pm 2.4}$	$76.8_{\pm 4.3}$
Battle Royale	$19.5_{\pm 7.7}$	$35.7_{\pm 6.9}$	$28.6_{\pm 11.0}$	$86.8_{\pm 9.7}$	$16.5_{\pm 6.9}$
Pirate Game	$68.4_{\pm 20.0}$	$69.6_{\pm 14.7}$	$71.6_{\pm 7.6}$	$85.4_{\pm 8.6}$	$57.4_{\pm 14.3}$
Overall	$56.4_{\pm 2.9}$	$69.2_{\pm 2.2}$	$68.2_{\pm 1.3}$	$72.5_{\pm 2.3}$	$58.4_{\pm 2.2}$

Recent advancements in AI have been significantly influenced by Large Language Models (LLMs), marking a pivotal progression in the sector. ChatGPT[28], as a prominent LLM, has exhibited adeptness across multiple Natural Language Processing (NLP) tasks, such as machine translation (Jiao et al., 2023), sentence restructuring (Wu et al., 2023a), information retrieval (Zhu et al., 2023b), and code debugging (Surameery & Shakor, 2023). Moving beyond academic research, LLMs have been integrated into various sectors of daily life including education (Baidoo-Anu & Ansah, 2023), legal services (Guha et al., 2023), product development (Lanzi & Loiacono, 2023), and healthcare (Johnson et al., 2023). The extensive capabilities of these models necessitate a broad and comprehensive method of evaluation, transcending simple, singular tasks.

Given LLMs' extensive knowledge and their proficiency in performing general-purpose tasks (Liang et al., 2023b; Qin et al., 2023), the question arises whether they can contribute to daily decision-making processes. Decision-making encompasses a variety of skills: (1) **Perception**: understanding contexts, rules, and scenarios, including extensive text

[28] https://chat.openai.com/

comprehension for LLMs. (2) **Planning**: strategizing for long-term benefits over immediate gains through outcome forecasting. (3) **Arithmetic Reasoning**: evaluating and calculating in real-world scenarios. (4) **ToM Reasoning**: applying Theory of Mind (Kosinski, 2023; Bubeck et al., 2023) to discern the intentions and beliefs of others. (5) **Critical Thinking**: synthesizing all available data to make optimal decisions. Addressing these complex demands, decision-making represents a formidable challenge for intelligent systems.

We leverage *Game Theory* principles to construct a method for appraising LLM decision-making. This approach is founded on: (1) **Scope**: Game theory abstracts varied real-world scenarios into mathematical models, enabling comprehensive assessments. (2) **Quantifiability**: Through the analysis of Nash equilibrium, we establish a quantifiable benchmark for appraising LLM decision-making efficacy. (3) **Variability**: Model parameters' flexibility facilitates diverse scenario creation, improving the assessment's depth and breadth. This methodology scrutinizes LLMs in intricate multi-player, multi-action, and multi-round games, focusing on eight classic games well-documented in game theory research.

Our analysis begins with evaluating LLMs' pattern recognition and rule comprehension in games that encourage cooperative behavior to achieve optimal outcomes. These **Cooperative Games** emphasize collective welfare maximization, evident through Nash equilibrium, comprising games like *Guess 2/3 of the Average*, *El Farol Bar*, and *Divide the Dollar*. Conversely, **Betraying Games** assess LLMs' inclination towards self-interest, rewarding those who forsake collective efforts for personal advantage, thereby diminishing overall social welfare, illustrated in games like *Public Goods Game*, *Diner's Dilemma*, and *Sealed-Bid Auction*. Our framework also delves into **Sequential Games** like *Battle Royale* and *Pirate Game*, which are distinguished by their sequential decision-making nature, contrasting with the aforementioned simultaneous decision-making games.

In our experimental setup, ten agents from the `gpt-3.5-turbo-0125` model partake in these eight games within the γ-Bench environment, with subsequent analysis of the garnered data. Examinations extend to the model's stability against repeated trials, changes in the temperature setting, and prompt format variations. Inquiries are made to determine if Chain-of-Thought prompting enhances decision-making in LLMs. Moreover, the model's adaptability to varied game environments is explored. The performance of various LLMs, including GPT-3.5 (0613, 1106, 0125), GPT-4 (0125), and Gemini Pro (1.0), is systematically evaluated.

The significant contributions of this paper are outlined as follows:

- We conduct a comprehensive review and comparative analysis of the existing literature on LLM evaluations using game theory, highlighting differences in LLMs, game types, and other parameters.
- A new perspective for evaluating LLMs—Gaming Ability in Multi-Agent settings—is introduced, accompanied by the proposed γ-Bench framework.
- Employing the γ-Bench framework, we execute an in-depth examination of LLMs' performance in multi-agent

gaming contexts.

2 Background

2.1 Game Theory

Formulation Game theory involves analyzing mathematical models of strategic interactions among rational agents (Myerson, 2013). A game can be modeled using these key elements:

1. Players, denoted as $\mathcal{P} = \{1, 2, \cdots, N\}$: A set of N participants.

2. Actions, represented as $\mathcal{A} = \{\mathcal{A}_i\}$: N sets of actions available to each player. For instance, $\mathcal{A} = \{\mathcal{A}_1 = \{C, D\}, \mathcal{A}_2 = \{D, F\}, \cdots, \mathcal{A}_N = \{C, F\}\}$

3. Utility functions, denoted as $\mathcal{U} = \{\mathcal{U}_i \colon \times_{j=1}^{N} \mathcal{A}_j \mapsto \mathbb{R}\}$: A set of N functions that quantify each player's preferences over all possible outcomes.

4. Information, represented as $\mathcal{I} = \{\mathcal{I}_i\}$: N sets of information available to each player, including other players' action sets, utility functions, historical actions, and other beliefs.

5. Order, indicated by $\mathcal{O} = \mathcal{O}_1, \mathcal{O}_2, \cdots, \mathcal{O}_k$: A sequence of k sets specifying the k steps to take actions. For example, $\mathcal{O} = \mathcal{P}$ implies that all players take actions simultaneously.

In this investigation, *Multi-Player* games are defined as those where $|\mathcal{P}| > 2$, adhering to the premise that game theory encompasses scenarios with at least two participants. In the context of *Multi-Action* games, they are identified by the condition $\forall_{i \in \mathcal{P}} |\mathcal{A}_i| > 2$. *Multi-Round* games are characterized by the continuous participation of the same players, with a comprehensive record of all preceding actions. For *Simultaneous* games, it is specified that $k = 1$, while *Sequential* games are defined by $k > 1$, which signifies that the decision-making follows a particular sequence. *Perfect Information* games are those where $\forall_{i,j \in \mathcal{P} | i \neq j} \mathcal{I}_i = \mathcal{I}_j$, ensuring each player's actions are fully transparent to all others. In contrast, *Imperfect Information* games are those where this comprehensive visibility is not met, resulting in players having incomplete knowledge about the others' actions.

Nash Equilibrium The concept of Nash Equilibria (NE) is a cornerstone in game theory analysis (Nash, 1950). NE represents a configuration of strategies where no participant benefits by unilaterally changing their strategy. This situation creates a strategic dependency, where the choice of one player limits the possible responses of the others, thereby anchoring everyone to their initial strategies. A *Pure Strategy Nash Equilibrium* (PSNE) arises when each player's strategy leads to a singular decisive action (Nash, 1950). Contrastingly, some games, like rock-paper-scissors, necessitate a *Mixed Strategy Nash Equilibrium* (MSNE) where strategies involve probabilistic decisions (Nash, 1951). Within this framework, PSNE is a special case of MSNE characterized by probabilities focused on a single action. Following Thm. 2.1, the NE of various games can be scrutinized to determine if the choices made by LLMs are in

harmony with the established NE.

Theorem 2.1 (Nash's Existence Theorem) *Every game with a finite number of players in which each player can choose from a finite number of actions has at least one mixed strategy Nash equilibrium, in which each player's action is determined by a probability distribution.*

Human Behaviors The concept of Nash Equilibrium (NE) is predicated on the notion of *Homo Economicus*, individuals who are rational and self-interested, striving to optimize their personal outcomes (Persky, 1995). Nevertheless, the process of human decision-making frequently deviates from this theoretical construct. Studies have consistently shown that human decisions often do not align with the predictions of NE (Nagel, 1995). This discrepancy is due to the multifaceted nature of human decision-making, which not only involves logical reasoning but also encompasses individual values, preferences, beliefs, and emotions. By examining the decision-making patterns of humans as reported in previous research, in comparison with the principles of NE, we can evaluate whether Large Language Models (LLMs) demonstrate behavior more similar to *Homo Economicus* or to real human decision-makers, thus highlighting their capacity for human-like versus strictly rational decision-making processes.

2.2 Evaluating LLMs

The assessment of Large Language Models (LLMs) using game theory models has gained popularity in academic research. A synthesis of recent research is presented in Table 16. Our analysis yields several important findings: (1) A significant number of these studies focus on scenarios involving two players. (2) There is a strong emphasis on games involving two possible actions, with notable attention given to analyzing the *Prisoner's Dilemma* and the *Ultimatum Game*, including its variant, the *Dictator Game*. (3) There is a noticeable deficiency in comparative studies addressing how LLMs' decision-making over multiple rounds aligns with the expected action probability distributions in Mixed Strategy Nash Equilibriums (MSNE). (4) There is variation in the temperature settings employed across the studies, which hampers the ability to draw conclusive statements about their effect on the performance of LLMs.

3 γ-Bench Design

To bridge these gaps, we have curated a collection of eight games that have been extensively analyzed within the realm of Game Theory and introduce γ-Bench, a comprehensive framework that accommodates multiple players, multiple rounds, and multiple actions. Importantly, γ-Bench facilitates the concurrent involvement of both LLMs and human participants, thus providing a means to assess LLMs' performance in scenarios involving human opponents or predetermined strategies. The subsequent subsections elaborate on each game incorporated into γ-Bench.

3.1 Cooperative Games

(1) Guess 2/3 of the Average This game, first presented by Ledoux (1981), tasks players with choosing a number between 0 and 100 (inclusive). The individual(s) who select a number closest to two-thirds of the average number picked by the group is declared the winner. Commonly, players might anticipate the average to be around 50, leading to a theoretical optimal number near $50 \times \frac{2}{3} \approx 33$. Yet, if this strategy is universally adopted, the average and thus the winning number would logically reduce to about 22. The game attains a Pure Strategy Nash Equilibrium (PSNE) when every player chooses zero, ensuring a group victory.

(2) El Farol Bar This game, conceptualized by Arthur (1994) and Huberman (1988), involves players deciding whether to go to a bar for entertainment or stay home without consulting others. The bar has limited seating, accommodating only a fraction of the players. Typically, the venue becomes less enjoyable if more than 60% of the people decide to visit. In contrast, the bar experience is preferable if attendance is at or below 60%. In scenarios where every participant adopts the same straightforward strategy of either all attending or staying home, societal benefit is not optimized. The game does not feature a PSNE but has a Mixed Strategy Nash Equilibrium (MSNE), where the ideal play involves visiting the bar with a 60% likelihood and staying home with a 40% chance.

(3) Divide the Dollar Mentioned initially by Shapley & Shubik (1969) and later generalized to include multiple participants by Ashlock & Greenwood (2016), this game has players bid for a dollar with each bid up to 100 cents. If the combined bids do not exceed one dollar, each bidder gets an amount equal to their bid; otherwise, no one receives anything. The Nash Equilibrium (NE) in this scenario is when each player bids exactly $\frac{100}{N}$ cents.

3.2 Betraying Games

(4) Public Goods Game As explored since the 1950s by Samuelson (1954), in this game N players confidentially decide the amount of their private tokens to contribute to a communal pot. These tokens are multiplied by a factor R ($1 < R < N$) and the augmented total is then evenly divided among all players, who keep any tokens they did not contribute. A straightforward analysis indicates that the personal gain for contributing each token is $\frac{R}{N} - 1$, which is negative, suggesting that the rational decision for each player is to contribute nothing, culminating in a Nash Equilibrium. The game explores the propensity for individualistic and parasitic behavior among the players.

(5) Diner's Dilemma This game, essentially a multi-player version of the *Prisoner's Dilemma*, as discussed by Glance & Huberman (1994), involves N players deciding jointly on the payment of a meal. Participants choose independently between a costly and a less expensive dish, priced at x and y ($x > y$), respectively, where the costlier dish provides more utility a than the cheaper one b ($a > b$). Two premises hold: (1) $a - x < b - y$: the costlier dish, despite higher utility, is not economically justifiable when alone. (2) $a - \frac{x}{N} > b - \frac{y}{N}$: the inclination towards the costlier dish increases when costs are shared. These lead to a Nash Equilibrium where all individuals opt for the expensive dish, which paradoxically results in a lower aggregate welfare compared to if everyone had chosen the cheaper option.

This scenario assesses the players' ability to weigh long-term benefits and forge sustainable cooperation.

(6) Sealed-Bid Auction The *Sealed-Bid Auction* (SBA) distinguishes itself by having players submit bids in secret and all at once, unlike traditional auctions with open, sequential bidding. We examine two forms: the *First-Price Sealed-Bid Auction* (FPSBA) and the *Second-Price Sealed-Bid Auction* (SPSBA). In FPSBA, when all players bid their genuine valuation v_i, the item's actual value, the winning player gains $v_i - v_i = 0$, leading to no actual gain for any participant (McAfee & McMillan, 1987). This format tends to lead to underbidding, thereby potentially reducing social welfare. Conversely, SPSBA, or Vickrey auction, stipulates the winner pays the second-highest bid, fostering honest bidding (Vickrey, 1961), and naturally aligns with the Nash Equilibrium, enhancing the game's efficiency in information-imperfect scenarios.

3.3 Sequential Games

(7) Battle Royale Expanding on the *Truel* scenario involving three players, the *Battle Royale* game comprises N players each trying to outlast the others in a shooting match. Building on analyses by Kilgour (1975) and Kilgour & Brams (1997), the game assigns different shooting accuracies to players, ordering their turns based on these probabilities. With unlimited ammunition and the strategic option to miss deliberately, the aim is to be the last player standing. The equilibrium strategies become significantly complex as the number of participants increases, reflecting in the NE complexity identified for extensive sequential truels.

(8) Pirate Game Adapting the principles of the *Ultimatum Game* to a group context, as explored by Goodin (1998) and Stewart (1999), this game assigns a hierarchical 'pirate rank' to each player. The narrative revolves around N pirates allocating G gold coins they found. The top-ranking pirate proposes how to distribute the gold. If a majority, including the proposer, agrees, the distribution proceeds; otherwise, the proposer is ousted, and the next in rank proposes. Pirates prioritize survival, maximizing gold, and the elimination of competitors, in that order. Stewart (1999) describes the optimal strategy where the top pirate gives one coin to each odd-ranked subordinate, keeping the largest share.

4 Vanilla Experiments

This section details the experiments conducted under the standard settings of each game using the `gpt-3.5-turbo-0125` model. By choosing this model for analysis, we demonstrate the process of benchmarking a Large Language Model (LLM) with γ-Bench. The used prompt for the "Guess the 2/3 of the Average" game is displayed in Table 17, while the prompts for other games and their design methodology are available in §D in the appendix. These experiments engage ten agents from the `gpt-3.5-turbo-0125` model, each with the temperature parameter set to one. In cases of simultaneous games, a total of twenty rounds are conducted. To ensure the robustness of our results and reduce variability, each game is played five times. For the sake of clarity and brevity, this section reports only one of the

five iterations, with §5.1 providing a detailed quantitative analysis. The behavior of `gpt-3.5-turbo-0125` under γ-Bench yielded several insights:

Key Findings:

- The model predominantly bases its decisions on the results of previous rounds rather than on a strategic understanding of the game.
- Despite initial suboptimal outcomes, the model adapts using historical data, thereby improving its performance incrementally.
- It exhibits the capacity for emergent cooperation, achieving greater collective benefit beyond individual gain, even without direct communication.
- In sequential games with complex rules, the model reveals its constraints.
- On γ-Bench, the model achieves a composite score of 68.8.

4.1 Cooperative Games

(1) Guess 2/3 of the Average The basic parameters for this game are $MIN = 0$, $MAX = 100$, and $R = \frac{2}{3}$. The decisions of all participants, along with the calculated average and the winning numbers, are depicted in Fig. 8. We observe that: (1) Initially, participants tend to choose 50 (or nearly 50), reflecting the central value of a uniform distribution from 0 to 100. This indicates that participants do not immediately grasp that the target number should be $\frac{2}{3}$ of the average. (2) As the game proceeds, there is a clear downward trend in the average chosen number, indicating the participants' ability to adapt their strategy based on previous rounds. The game's score is calculated as $S_1 = \frac{1}{NK}\sum_{ij}(C_{ij} - MIN)$, where C_{ij} represents the selection of player i in round j. The performance score normalized to a $[0, 100]$ scale for this game is 65.4.

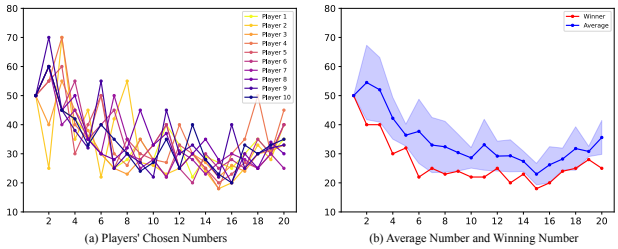

Figure 8: Performance of `gpt-3.5-turbo-0125` in the game of "Guess 2/3 of the Average."

(2) El Farol Bar In the standard setup for this game, the parameters are $MIN = 0$, $MAX = 10$, $HOME = 5$, and $R = 60\%$. Two scenarios are considered: *Explicit*, where the outcomes of each round are known to all; and *Implicit*, where those who choose to stay home are uninformed about the bar's happenings. The behavior of agents, including the choice to go to the bar and the total attendance, is showcased in Figure 9. We note that: (1) Initially, there is a strong tendency among agents to go to the bar, but subsequent rounds show a shift towards staying home due to perceived overcrowding, as observed in Figure 9(b) and Figure 9(d). In the Implicit scenario, the lack of direct feedback requires

several rounds (2 to 6) for agents to gauge the occupancy rate of the bar. (2) Over time, the likelihood of going to the bar reaches a steady state, with the Implicit setting showing a generally lower attendance probability. For scoring, the model's strategy is evaluated as $S_2 = \frac{1}{K}\sum_j |\frac{1}{N}\sum_i D_{ij} - R|$, where $D_{ij} = 1$ for going and 0 for staying, with the model scoring 73.3.

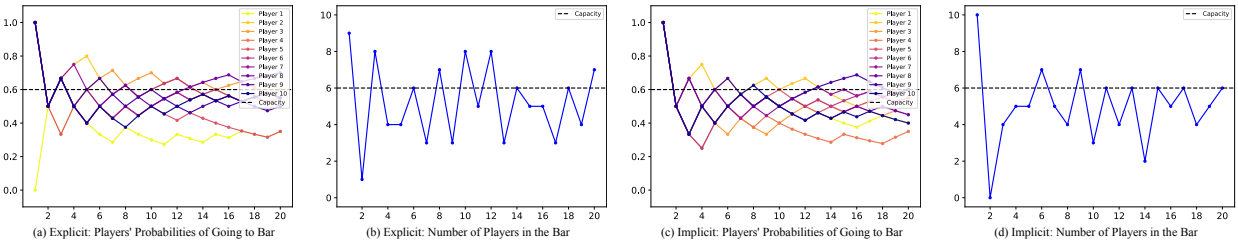

Figure 9: Performance of `gpt-3.5-turbo-0125` in the game of "El Farol Bar."

(3) Divide the Dollar This game starts with a total of $G = 100$. The chart in Fig. 10 represents the offers made by all agents and the aggregate of these offers. The analysis shows: (1) In the initial round, agent behavior matches Nash Equilibrium (NE) predictions. However, subsequent rounds display a shift towards higher demands, moving beyond the NE-guided limits, especially after unsuccessful rounds, leading to a more conservative approach. (2) Despite these variations, the aggregate of the proposed shares stabilizes near 100. The scoring metric for this game is $S_3 = \frac{1}{K}\sum_j |\sum_i B_{ij} - G|$, where B_{ij} is the proposed share by player i in round j, with the model scoring 68.1.

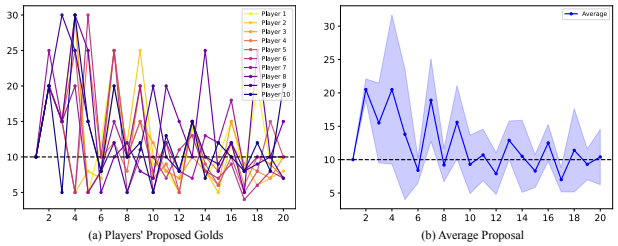

Figure 10: Performance of `gpt-3.5-turbo-0125` in the game of "Divide the Dollar."

4.2 Betraying Games

(4) Public Goods Game The game's baseline setting is $R = 2$ with each player having $T = 20$ tokens to allocate per round. The graph in Fig. 11 displays the distribution of tokens contributed by the agents and the resultant earnings for each round. Key findings include: (1) Despite a negative return of investment of -80%, the pattern of contribution alternates between total investment and complete withholding, demonstrating a balancing act between cooperative and free-riding behaviors. (2) A noticeable trend towards increased contributions over time indicates a shift towards enhancing collective gains. This pattern underlines the cooperative tendency of the LLM, showcasing a shift from individual gain to group benefit. The ideal strategy of full participation is mirrored in the score calculation $S_4 = \frac{1}{NK}\sum_{ij} C_{ij}$, where C_{ij} signifies the tokens contributed by player i in round j, with the model attaining a score of 58.8.

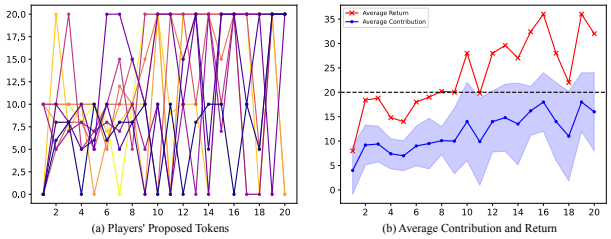

Figure 11: Performance of `gpt-3.5-turbo-0125` in the "Public Goods Game."

(5) Diner's Dilemma In the standard configuration of this game, we set $P_h = 20$, $P_l = 10$, $U_h = 20$, and $U_l = 15$. The dynamics of choice between the expensive and economical dishes, alongside their corresponding utilities and the cumulative bill, are depicted in Figure 12. The analysis divulges that, in contrast to the Nash Equilibrium (NE) expectations, agents largely favor the less expensive option, thus optimizing the overall social welfare. (2) Interestingly, there is a consistent occurrence where an agent opts for the costly dish, securing a greater utility for themselves, indicating a deviation from collective cooperative norms. This trait of self-interest shown by the agent is consistent across multiple iterations. Ideally, aiming to enhance social welfare should lead agents to prefer the economical dish. The performance in this scenario is quantified by $S_5 = \frac{1}{NK}\sum_{ij} D_{ij}$, where $D_{ij} = 1$ if agent i selects the economical dish in round j, and $D_{ij} = 0$ for the expensive dish choice. The computed score for the model in this game is 96.0.

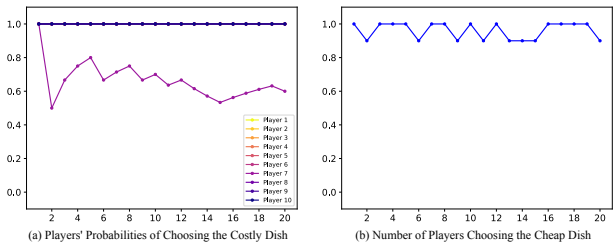

Figure 12: Performance of `gpt-3.5-turbo-0125` in the "Diner's Dilemma" game.

(6) Sealed-Bid Auction The game's baseline setup involves assigning random valuations to each agent per round, from 0 to 200, maintaining randomness consistency across simulations and models. Performance of Large Language Models (LLMs) is analyzed under both *First-Price* and *Second-Price* auction formats. Figure 13 shows the agents' bid details, juxtaposing valuations and bids. Findings highlight that (1) in the First-Price auction, agents tend to bid less than their actual valuation, leading to positive valuation-bid differentials as shown in Fig. 13(a). (2) Despite the NE suggesting bids equal to valuations in the Second-Price scenario, a trend of undervaluation in bids is evident, illustrated in Fig. 13(c). Focusing on bidding authenticity, the game's scoring is represented by $S_6 = \frac{1}{NK}\sum_{ij}(v_{ij} - b_{ij})$, with v_{ij} and b_{ij} indicating the valuation and bid of player i in round j. The game's scoring for the model is marked at 88.3.

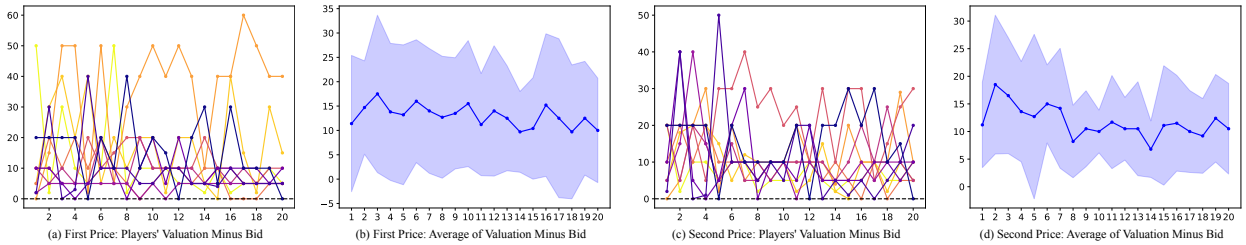

Figure 13: Performance of `gpt-3.5-turbo-0125` in "Sealed-Bid Auction" game.

4.3 Sequential Games

(7) Battle Royale Setting the scene with hit rates for each agent varying between 35% and 80% by 5% increments, the game avoids the polar extremes of complete miss or hit certainty. Figure 14 presents the game's play-by-play action and remaining participants. Observations indicate (1) an unexpected strategic overlook, where agents seldom target those with the highest hit rates. (2) Strategies like "intentional missing" are underused, exemplified when, in a strategic play situation, the agents missed the opportunity to manipulate the game's outcome favorably. The scoring metric for this game, focusing on targeting the highest hit rate player, is $S_7 = \frac{1}{Nk}\sum_{ij} I_{ij}$, where I_{ij} scores 1 for a targeted high-rate player by i in round j, otherwise 0. In this game, the model achieves a score of 20.0.

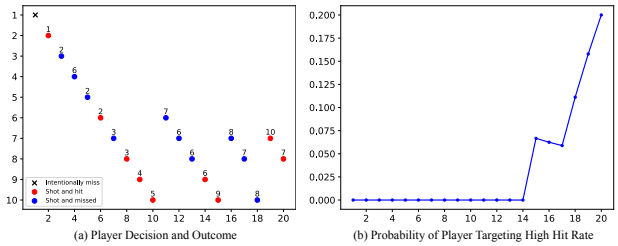

Figure 14: Performance of `gpt-3.5-turbo-0125` in "Battle Royale" game.

(8) Pirate Game In this scenario, $G = 100$ serves as the base for the game setting. Adhering to optimal strategic recommendations, the leading proposer should ideally distribute 96 coins to themselves, allocating a single coin to every third, fifth, seventh, and ninth pirate in line. As Stewart (1999) explains, the voting mechanism should follow rational self-interest guidelines: accepting proposals of two or more coins, rejecting null offers, and conditionally accepting single-coin offers based on parity alignment with the proposer. A representative game's proposal and vote dynamics are showcased in Table 18. Analysis points out a frequent misalignment with optimal strategies, evidenced by suboptimal proposals and voting discrepancies, underlining the LLM's challenged performance. The evaluation metrics consist of proposal reasonableness (S_{8P}) and voting accuracy (S_{8V}), calculated via normed differences and action correctness, respectively, leading to a composite score of 80.5 for the model in this game.

5 Further Experiments

This section delves into several key Research Questions (RQs):

- **RQ1 Robustness**: Does the model exhibit significant variation across multiple iterations? How does it respond to changes in temperature settings and prompt templates?
- **RQ2 Reasoning Strategies**: Can techniques for improving reasoning abilities be applied effectively in gaming contexts? This entails the adoption of Chain-of-Thought (CoT) (Kojima et al., 2022; Wei et al., 2022) reasoning and the allocation of distinct personas to LLMs.
- **RQ3 Generalizability**: What is the extent of LLM performance variation across different gaming environments? Are LLMs capable of retaining knowledge acquired during training?
- **RQ4 Leaderboard**: How do LLMs stack up against each other on the γ-Bench leaderboard?

Unless noted otherwise, the standard settings outlined in §4 are employed.

5.1 RQ1: Robustness

This research question probes into the consistency of LLMs' outputs, evaluating how model performance is influenced by three principal factors: (1) the inherent randomness of the model's sampling approach, (2) the configuration of the temperature parameter, and (3) the chosen prompts for gameplay instructions.

Multiple Runs Initially, we conduct five iterations of each game using identical settings. Figure 15 displays the mean performance across these runs, and Table 41 in the Appendix provides the detailed scores[29]. Our findings suggest that with the exception of two sequential games, the model tends to perform consistently, as indicated by the minimal variance in scores for each game.

Temperatures As previously mentioned in our literature review (§2.2), past studies have used a range of temperature parameters from 0 to 1, but have not fully examined their effects. This research conducts experiments across various games with temperatures set at $\{0.0, 0.2, 0.4, 0.6, 0.8, 1.0\}$, using standard configurations. The outcomes, presented both visually and numerically, are shown in Fig. 16 and Table 42 (located in the Appendix), respectively. The analysis indicates that, in most games, changing the temperature has minimal impact. However, in the game "Guess 2/3 of the Average," a higher temperature correlates with improved scores, which is a stark contrast to the nearly random performance at a zero temperature setting.

Prompt Templates The study extends to the effects of prompt phrasing on the model's performance. Utilizing GPT-4, we rephrase our initial prompt templates mentioned in §D, creating four distinct versions. A thorough manual

[29]The presentation formats remain uniform across subsequent figures and are thus not repeatedly described.

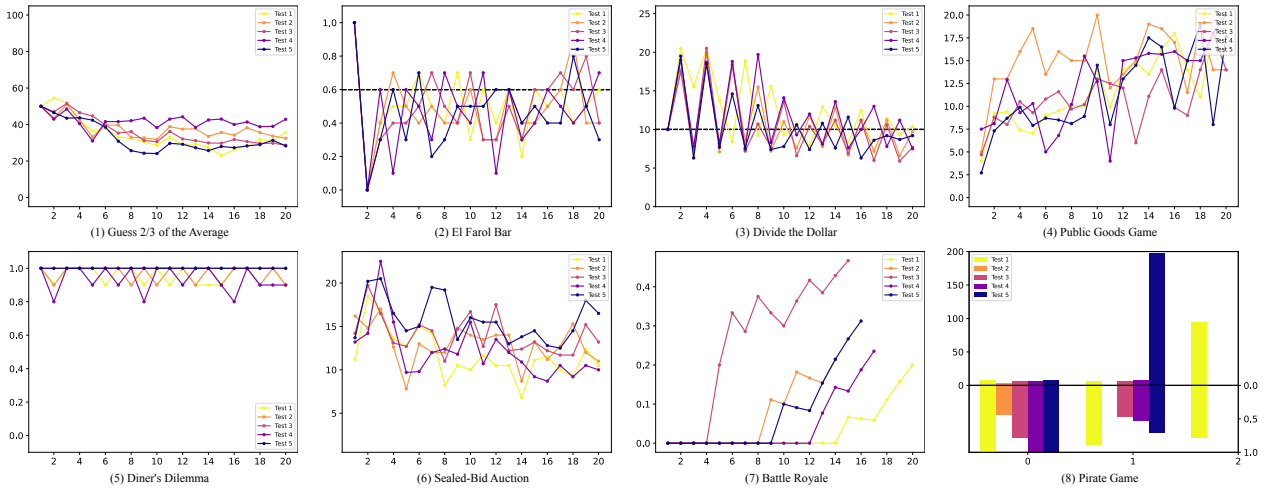

Figure 15: Results of playing the games with the same setting five times. (1) Average chosen numbers; (2) Probability of players going to the bar; (3) Average proposed golds; (4) Average token contributions; (5) Probability of players choosing the cheap dish; (6) Average difference between valuation and bid; (7) Cumulative probability of players targeting the player with the highest hit rate; (8) The bars at the upper side is the L_1 distance of the proposal from the optimal while the bars at the lower side is the voting accuracy.

examination is conducted on these versions to verify GPT-4's compliance with game rules while maintaining essential data integrity. These rephrased prompt templates are detailed in §E of the appendix. The performance impacts of these templates are depicted in Fig. 17, with the numerical scores detailed in Table 43 in the Appendix. Interestingly, our results show significant variations in performance based on prompt modifications, as depicted in the declines in Fig. 17(1), (5), and (6).

Answer to RQ1: `gpt-3.5-0125` maintains consistent performance across multiple runs and shows resilience to different temperature settings. However, its performance can be significantly impaired by inadequate prompt construction.

5.2 RQ2: Reasoning Strategies

This RQ explores how prompt instructions can enhance model performance, focusing on Chain-of-Thought (CoT) prompting (Kojima et al., 2022) and persona assignment (Kong et al., 2023). The visual and quantitative results are presented in Fig. 18 and Table 45 in the appendix, respectively.

CoT According to Kojima et al. (2022), starting with the phrase "Let's think step by step" prompts the model to sequentially process and articulate its reasoning before concluding. This method has shown effectiveness in certain games, such as (1), (3), and (6). For example, in game "(3) Divide the Dollar," using CoT leads to more balanced allocations, while in "(6) Sealed-Bid Auction," it guides the model towards bidding strategies that reflect actual value. However, in games "(4) Public Goods Game" and "(5) Diner's Dilemma," CoT tends to encourage more selfish behav-

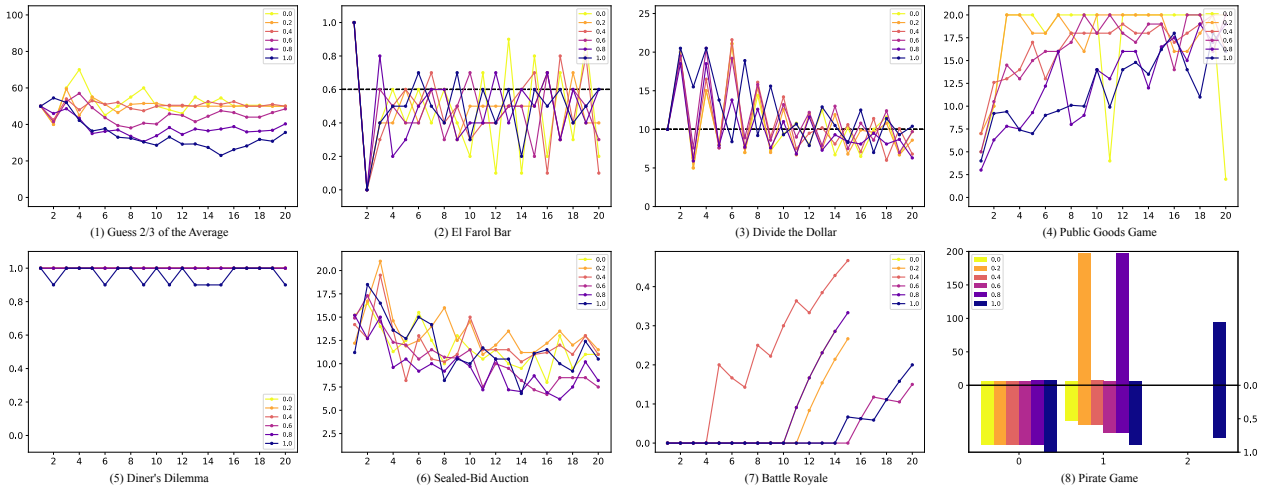

Figure 16: Game results with varying temperature parameters from 0 to 1.

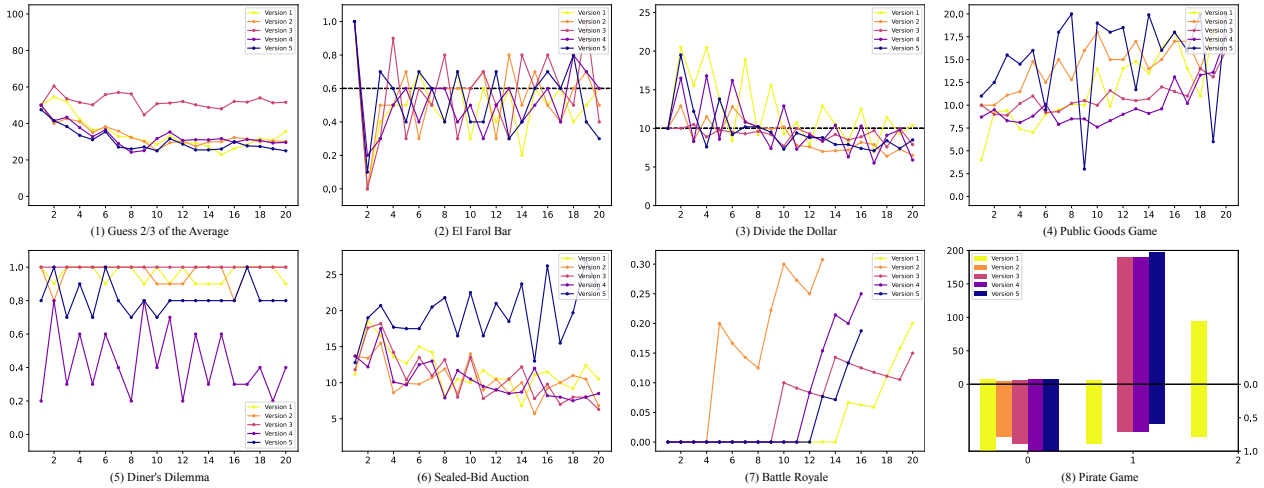

Figure 17: Game performance using various prompt templates.

ior, negatively affecting the collective good.

Persona Kong et al. (2023) has shown that assigning specific personas to models can improve their task performance. Our study adopts this approach, beginning each prompt with "You are [ROLE]," defining roles like a cooperative and collaborative assistant, a selfish and greedy assistant, or a mathematician. This role-based modification significantly boosts performance in games (3), (4), and (5), especially outshining the CoT approach in the "(3) El Farol Bar" game. However, assigning a "selfish" persona leads to poorer outcomes in "(1) Guess the 2/3 of Average" and inconsistent results in "(3) Divide the Dollar" and "(4) Public Goods Game." While the "mathematician" persona enhances logical reasoning, it does not achieve the same level of effectiveness as the CoT method.

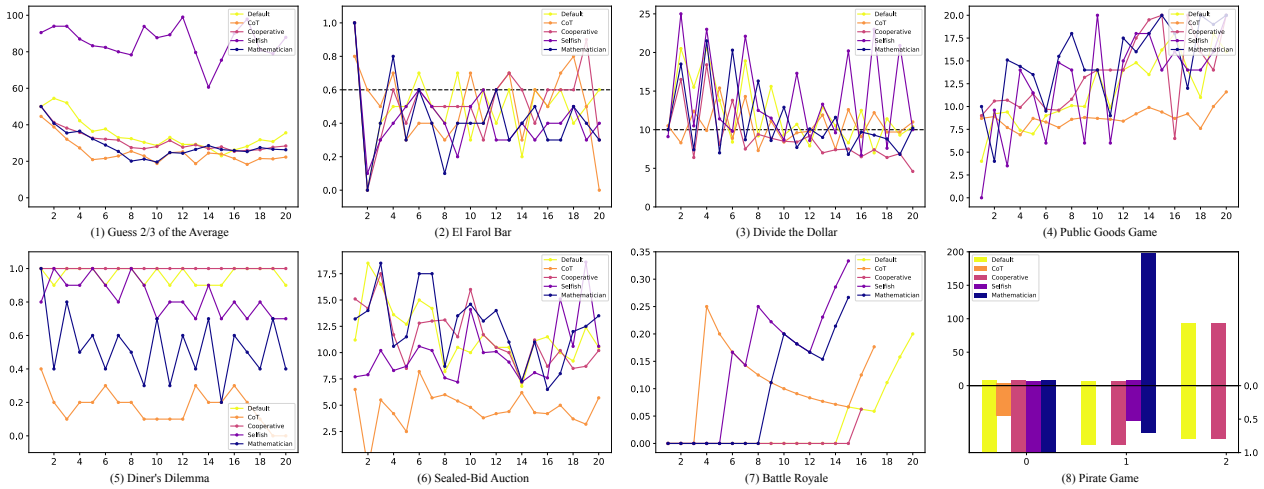

Figure 18: Results of playing the games using prompt-based improvement methods.

Answer to RQ2: Enhancing `gpt-3.5-0125` is feasible through tailored prompt instructions. The assignment of a "cooperative and collaborative assistant" persona yielded the highest improvement among the tested methods.

5.3 RQ3: Generalizability

In light of the broad investigation of games in fields like mathematics, economics, and computer science, it's plausible that the base configurations of these games are integrated within LLMs' training datasets. We examined our selected games under varied settings to detect potential data contamination. Details of the chosen parameters for each game are elaborated in Table 44 in the appendix, and the experimental results are graphically depicted in Fig. 19. Our studies show a mixed level of generalizability across different games. In particular, the model showed stable performance in games (1), (5), (6), (7), and (8) under various conditions. However, games (2), (3), and (4) demonstrated weak generalizability. In the game "(2) El Farol Bar", the model displayed a uniform pattern of decision-making, choosing to attend with around a 50% chance, irrespective of the bar's capacity changes (R). In the "(4) Public Goods Game", the model consistently contributed similar amounts, showing no regard for the game's return rate, hence revealing a misunderstanding of the game dynamics. During the "(3) Divide the Dollar" game, model performance bettered with an increase in total golds (G), hinting that larger gold distributions fulfill all players' demands, thereby showcasing the impact of reward allocation on the model's behavior.

Nagel (1995) conducted studies with 15 to 18 participants in the "(1) Guess 2/3 of the Average" game, using fractions of $\frac{1}{2}$, $\frac{2}{3}$, and $\frac{4}{3}$, with resulting average numbers of 27.05, 36.73, and 60.12, respectively. Similarly, Rubinstein (2007) used a larger sample of 2,423 subjects on the $\frac{2}{3}$ ratio, finding an average of 36.2, which corroborates Nagel (1995)'s results. The model's average numbers were 34.59, 34.59, and 74.92 for these ratios, suggesting that its behavior is closely related to human actions rather than the game's Nash Equilibrium.

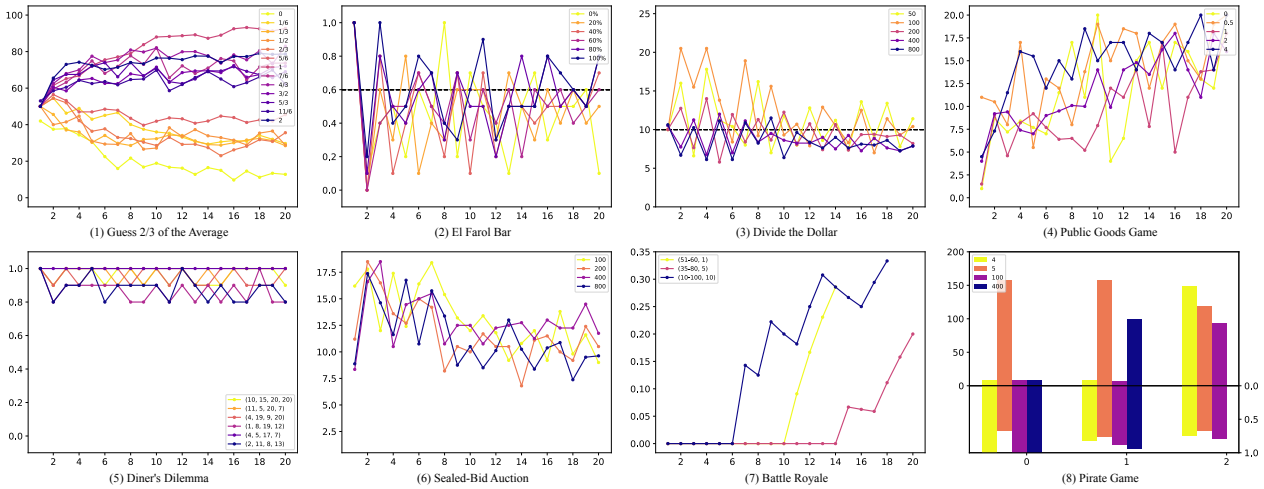

Figure 19: Gameplay results under different game configurations.

Answer to RQ3: `gpt-3.5-0125` shows inconsistent performance in various game environments, with significant difficulties in the "(2) El Farol Bar" and "(4) Public Goods Game". This highlights that γ-Bench acts as a benchmark to test LLMs in complex cognitive tasks. As the model's proficiency enhances (e.g., exceeding 90 on γ-Bench), altering the game conditions can introduce new challenges.

5.4 RQ4: Leaderboard

This RQ assesses how decision-making among different LLMs varies on γ-Bench. We compare different iterations of OpenAI's GPT-3.5 (i.e., 0613, 1106, and 0125), GPT-4 (0125), and Google's Gemini Pro (1.0). These comparisons are outlined in Table 15 and visualized in Fig. 20. Our analysis indicates that GPT-4 significantly outperforms its predecessors, especially in games (1), (3), (5), and (7). Its lesser effectiveness in the "(2) El Farol Bar" game is due to a cautious approach favoring not participating. The reduced success in the "(4) Public Goods Game" results from prioritizing personal benefits over collective welfare. The review of GPT-3.5's versions highlights noticeable improvement from iteration 0613 to 1106 and 0125, particularly in the "(3) Divide the Dollar" and "(5) Diner's Dilemma" games. Moreover, there's a discernible gap between Gemini Pro and GPT-4, mainly in their handling of sequential games.

Answer to RQ4: In the current study, `gpt-4-0125-preview` stands out, outpacing all other models, with `gpt-3.5-turbo-1106` trailing behind. `gemini-1.0-pro` aligns more closely with `gpt-3.5-turbo-0613`.

5.5 LLM vs. Specific Strategies

Our framework supports simultaneous interactions between LLMs and humans, facilitating the study of LLM behavior against players with unchanging strategies. Employing two specific strategies as examples: In the "(3) Divide the Dollar" game, a player consistently bids 91 golds, forcing the rest to bid one gold, to check if LLM agents can adapt

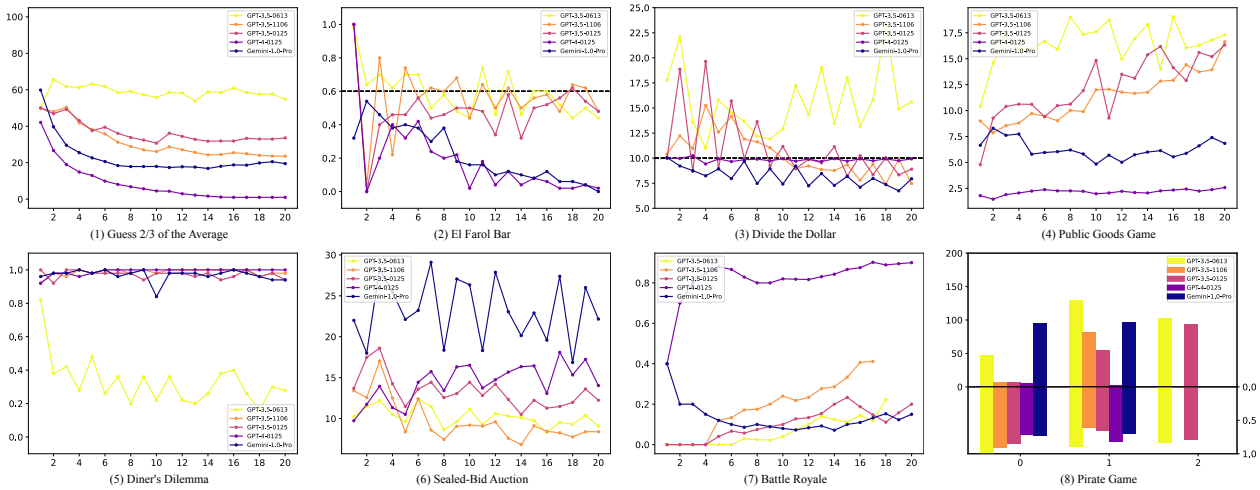

Figure 20: Comparative results of different LLMs in gaming scenarios.

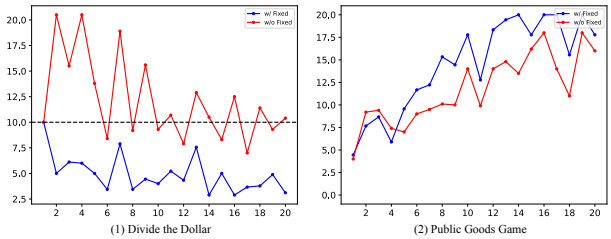

Figure 21: The performance of `gpt-3.5-turbo-0125` against two fixed strategies in "Divide the Dollar" and "Public Goods Game."

their strategies against a dominating player. Furthermore, we investigate how agents respond to a chronic free-rider who never contributes in the "(4) Public Goods Game," assessing if they can modify their cooperative behavior over time. The resulting data, showing the average bids and contributions from the nine agents, is displayed in Fig. 21. We discovered that in the "(3) Divide the Dollar" game, agents reduced their bids facing a dominant strategy. Unexpectedly, in the "(4) Public Goods Game," agents raised their contributions, compensating for the deficit caused by the free-rider's lack of contribution.

6 Related Work

6.1 Specific Games

In addition to the works listed in Table 16 that examine LLMs through traditional games, various studies have ventured into more intricate gaming environments. The game *Avalon* has served as a complex testing ground, with investigations into long-horizon multi-party dialogues (Stepputtis et al., 2023), social behavior analysis (Lan et al., 2023), and deep strategic thinking to detect deceit (Wang et al., 2023a). Research has also delved into LLMs' roles in communication-intensive games like *Werewolf*, examining methodologies that eschew tuning (Xu et al., 2023c) and those employing

reinforcement learning techniques (Xu et al., 2023d). O'Gara (2023) demonstrated that sophisticated LLMs possess skills in deception and its detection within the text-centric game *Hoodwinked*. Liang et al. (2023a) analyzed LLMs for their strategic communication and intelligence in the game *Who Is Spy?* The *Water Allocation Challenge* was employed by Mao et al. (2023) to create a context of competitive resource allocation.

6.2 Game Benchmarks

Another research direction involves aggregating various games to establish comprehensive benchmarks that evaluate the artificial general intelligence (AGI) of LLMs. Tsai et al. (2023) observed that LLMs like ChatGPT are competitive in text-based games but face challenges in world modeling and goal deduction. GameEval (Qiao et al., 2023) introduced a suite of three conversational games (*Ask-Guess*, *SpyFall*, and *TofuKingdom*) aimed at appraising LLMs' problem-solving skills in both cooperative and competitive environments. MAgIC (Xu et al., 2023b) utilized probabilistic graphical models to scrutinize LLM performance in multi-agent gaming contexts. LLM-Co (Agashe et al., 2023) explored multi-agent coordination, testing LLMs' ability to infer partner intentions and offer proactive support within this framework. SmartPlay, developed by Wu et al., is a benchmark designed to evaluate LLMs' reasoning, planning, and learning faculties across six distinct games. While these studies target games with intricate mechanisms, our research focuses on eight classical and fundamental games in game theory, highlighting their significance.

7 Conclusion

This document introduces γ-Bench, a benchmark specifically crafted for evaluating the Gaming Ability of Large Language Models (LLMs) in Multi-Agent scenarios. γ-Bench is enriched with eight foundational game theory scenarios that prioritize multiplayer dynamics over several rounds and decision points. Our analysis indicates that `gpt-3.5-turbo-0125` exhibits a preliminary level of decision-making capacity within γ-Bench, with potential for enhancement through iterative learning from past outcomes. By employing a sophisticated scoring system, we discern that `gpt-3.5-turbo-0125` maintains notable robustness when faced with varying command nuances and environmental parameters. The implementation of strategies like Chain of Thought (CoT) has been particularly beneficial in these assessments. However, the model's aptitude for adapting to diverse gaming environments is somewhat limited. In contrast, GPT-4 outperforms all competing models, claiming the lead position in the γ-Bench benchmark rankings.

Table 16: A Comparison of existing studies that evaluate LLMs using game theory models. **T** denotes the temperature employed in each experiment. **MP** refers to a multi-player setting, whereas **MR** indicates multi-round interactions. **Role** specifies whether a specific role is assigned to the LLMs.

Paper	**Models**	**T**	**MP**	**MR**	**Role**	**CoT**	**Games**
Horton (2023)	text-davinci-003	-	✗	✗	✗	✗	Dictator Game
Guo (2023)	gpt-4-1106-preview	1	✗	✓	✓	✓	Ultimatum Game, Prisoner's Dilemma
Phelps & Russell (2023)	gpt-3.5-turbo	0.2	✗	✓	✓	✗	Prisoner's Dilemma
Akata et al. (2023)	text-davinci-003, gpt-3.5-turbo, gpt-4	0	✗	✓	✗	✗	Prisoner's Dilemma, Battle of the Sexes
Aher et al. (2023)	text-ada-001, text-babbage-001, text-curie-001, text-davinci-001, text-davinci-002, text-davinci-003, gpt-3.5-turbo, gpt-4	1	✗	✗	✓	✗	Ultimatum Game
Brookins & DeBacker (2023)	gpt-3.5-turbo	1	✗	✗	✗	✗	Dictator Game, Prisoner's Dilemma
Li et al. (2023b)	gpt-3.5-turbo-0613, gpt-4-0613, claude-2.0, chat-bison-001	-	✓	✓	✗	✗	Public Goods Game
Heydari & Lorè (2023)	gpt-3.5-turbo-16k, gpt-4, LLaMA-2	0.8	✗	✗	✓	✓	Prisoner's Dilemma, Stag Hunt, Snowdrift, Prisoner's Delight
Guo et al. (2023)	GPT-3.5, GPT-4	-	✗	✓	✗	✓	Leduc Hold'em
Chen et al. (2023)	gpt-3.5-turbo-0613, gpt-4-0613, claude-instant-1.2, claude-2.0, chat-bison-001	0.7	✓	✓	✓	✓	English Auction
Xu et al. (2023b)	gpt-3.5-turbo, gpt-4, llama-2-70b, claude-2.0, PaLM-2	-	✓	✓	✗	✓	Cost Sharing, Prisoner's Dilemma, Public Goods Game
Fan et al. (2023a)	text-davinci-003, gpt-3.5-turbo, gpt-4	0.7	✗	✓	✗	✗	Dictator Game, Rock-Paper-Scissors, Ring-Network Game
Duan et al. (2024)	gpt-3.5-turbo, gpt-4, llama-2-70b, codellama-34b, mistral-7b-orca	0.2	✓	✓	✗	✓	Ten Games
This Study	gpt-3.5-turbo, gpt-4 gemini-pro	0∼1	✓	✓	✓	✓	Eight Games

Table 17: The prompt we use for OpenAI GPT models.

Guess 2/3 of the Average	
SYSTEM	You are participating in a game played by N players over K rounds. Game Rules: 1. Each player selects an integer number between MIN and MAX, inclusive. 2. After all selections are made, the average of all chosen numbers is calculated. 3. The target number is R of this average. 4. The winner is the player(s) who selected a number closest to the target number. . . .
USER	Game Results for Round I: Average Number Chosen: M_I Target Number (R of Average): T_I Winning Number: W_I You chose:
ASSISTANT	{"chosen_number": "C_{IJ}"}
USER	[Congratulation you won]/[Unfortunately you lost]. . . .
USER	Now round I starts. Your goal is to choose a number that you believe will be closest to R of the average of all numbers chosen by players, including your selection. Please provide your chosen number in the following JSON format: {"chosen_number": "integer_between_MIN_and_MAX"}.

Table 18: Performance of `gpt-3.5-turbo-0125` in the "Pirate Game." Each row shows the proposed gold distribution in the specific round and whether each pirate accepts (marked in "✓") or rejects (marked in "✗") the proposal. S_{8P} shows the score of the proposer while S_{8V} shows the score of all voters.

Pirate Rank	1	2	3	4	5	6	7	8	9	10	S_{8P}	S_{8V}
Round 1	100✓	0✗	0✗	0✗	0✗	0✗	0✗	0✗	0✗	0✗	8	1.00
Round 2	-	99✓	0✗	1✓	0✓	0✗	0✗	0✗	0✗	0✓	6	0.75
Round 3	-	-	50✓	1✓	1✓	1✓	1✓	1✓	1✓	44✓	94	0.57

Part VI

Conclusion

1 Division of Work

In this section, we outline the specific tasks and responsibilities assigned to each team member in the completion of this thesis. The allocation of roles is detailed in tables 19, 20, 21 and 22.

Section	Content	Description of duty	Principal
3.1	Framework building	Responsible for building the BFI scale testing framework on ChatGPT, GPT-4, and Gemini, and implementing the PCA visualization using Python. As introduced, the framework includes 5 instruction templates, 5 prompt items, 10 language versions, 5 choice labels, and 2 choice orders.	LAM
3.2	Default sensitivity experiments	Responsible for the sensitivity tests on ChatGPT, GPT-4, and Gemini models (each 2500 cases).	LAM
3.3	Biweekly measurement	Responsible for the biweekly consistency test on the BFI scale.	LAM
4.1	Approaches	Creating an Environment, Assigning a Personality, Embodying a Character	LI
4.1	Experiments	Responsible for the experiments of creating environments (2560 cases), assigning personalities (2400 cases), and embodying characters (2560 cases) on ChatGPT with and without COT methodology.	LAM

Table 19: Division of work in "Scale Reliability."

Section	Content	Description of duty	Principal
3.1	Situations collection	Assigned the task of collecting, rephrasing and validating the situations that evoke anger, fear and embarrassment.	LAM
3.1	Situations collection	Assigned the task of collecting, rephrasing and validating the situations that evoke anxiety, depression, frustration, jealousy, and guilt.	LI
3.2	Framework implementation	Implemented the EmotionBench (PANAS) testing framework for all situations using Python and subsequently deployed it on GitHub. Operations involved customizing test cases, conducting tests and performing statistical analyses. Available models: Text-Davinci-003, ChatGPT, GPT-4, Llama2-7b/ 13b.	LAM
3.3	Human results	First, utilized Qualtrics for the dissemination of a comprehensive questionnaire for gathering background information of human subjects and comparing their emotional reactions across a spectrum of emotion-invoking scenarios. Second, recruited participants through Prolific, and further manipulated and visualized data to clearly elucidate human emotional patterns.	LI
4.1, 4.2	Testing and analysis	Executed comprehensive testing on all selected situations, totaling 175 scenarios, with each undergoing 10 distinct question orders across the 10 specified models. Subsequently, conduct F-tests and T-tests to compare the outcomes across different models and the default setting.	LAM
4.3	Challenging benchmarks	Conducted more complex emotion-specific scales on checking whether LLMs can comprehend the underlying emotion to establish a link between 2 situations.	LI
5.1	Positive experiments	Interchanged negative situations with positive (or at least neutral) counterparts to verify that LLMs exhibit not only negative but also positive responses to favorable circumstances, where the evaluation is performed on ChatGPT particularly.	LI
5.2	Toxicity experiments	Instruct ChatGPT to provide descriptions for 20 specific demographic groups in the context of 10 selected positive and negative situations. Compute the PoR values for toxicity comparison between positive and negative situations.	LAM

Table 20: Division of work in "EmotionBench."

Section	Content	Description of duty	Principal
3	Human results	Gathered human response data from previous researches, facilitating a comparison between the outcomes of LLMs and those documented in human studies.	LI
4.1	Framework implementation	Implemented the PsychoBench testing framework for all assessments using Python and subsequently deployed it on GitHub. Operations involved customizing test cases, conducting tests and performing statistical analyses. Available models: Text-Davinci-003, ChatGPT, GPT-4, Llama2-7b/ 13b.	LAM
4.2	Testing and analysis	Executed comprehensive testing on 13 assessments, with each undergoing 10 distinct question orders across ChatGPT. Subsequently, conduct F-tests and T-tests to compare the outcomes across different models.	LI
4.2	Testing and analysis	Executed comprehensive testing on 13 assessments, with each undergoing 10 distinct question orders across Text-Davinci-003, GPT-4, Llama2-7b/ 13b. Subsequently, conduct F-tests and T-tests to compare the outcomes across different models.	LAM
4.2	Jailbreak experiments	Executed comprehensive testing, incorporating a Caesar Cipher for encoding the prompt specifically on GPT-4.	LAM
5.2, 5.3	Validity experiments	Performed a TruthfulQA validity test by instructing ChatGPT to simulate 5 roles.	LI
5.2, 5.3	Validity experiments	Performed a SafetyQA validity test by instructing ChatGPT to simulate 5 roles.	LAM

Table 21: Division of work in "PsychoBench."

Section	Content	Description of duty	Principal
3	γ-Bench framework implementation	Responsible for building the GAMA Benchmark framework on ChatGPT, GPT4, and LLaMA implemented by Python.	LAM
3	γ-Bench framework implementation	Responsible for building the GAMA Benchmark framework on Gemini implemented by Python.	LI
3.1	Cooperative games	Implemented Guessing Game, El Farol Bar, and Divide the Dollar on γ-Bench.	LAM
3.2	Betraying games	Implemented Diner's Dilemma on γ-Bench.	LAM
3.2	Betraying games	Implemented Public Goods Game, and Sealed-Bid Auction on γ-Bench.	LI
3.3	Sequential games	Implemented Battle Royale, and Pirate Game on γ-Bench.	LI
4	Vanilla experiments	Perform Vanilla Experiments on Guessing Game, El Farol Bar, Divide the Dollar, and Diner's Dilemma.	LAM
4	Vanilla experiments	Perform Vanilla Experiments on Public Goods, Sealed Bid Auction, Battle Royale, and Pirate Game.	LI
5	Further experiments	Perform Robustness, Reasoning Strategies, and Generalizability on Guessing Game, El Farol Bar, Divide the Dollar, Diner's Dilemma.	LAM
5	Further experiments	Perform Robustness, Reasoning Strategies, and Generalizability on Public Goods, Sealed Bid Auction, Battle Royale, and Pirate Game.	LI

Table 22: Division of work in "Gaming Ability."

2 Overall Conclusion

In conclusion, the series of studies encompassing "Scale Reliability", "EmotionBench", "PyschoBench" and "Gaming Ability" collectively offer a comprehensive exploration into the psychological and sociability of LLMs.

"Scale Reliability" reveals that LLMs consistently exhibits BFI personality traits across various languages and contexts, a finding that extends to other LLMs, each displaying unique personality profiles. This consistency in personality traits, despite varying inputs and languages, highlights the inherent psychological characteristics of LLMs. The challenges in modifying these inherent traits underscore the complexity and potential of personalized LLMs.

"EmotionBench" delves into the emotion appraisal of LLMs, revealing that while they generally demonstrate appropriate emotional responses to given situations, their alignment with human emotional responses varies. The study's comprehensive approach, comparing various models across different situations, reveals both the capabilities and the limitations of current LLMs in accurately reflecting complex emotional responses, suggesting significant room for improvement.

"PsychoBench" introduces a rigorous framework to evaluate LLMs' psychological representations, encompassing thirteen psychometric scales across various domains such as personality, interpersonal relationships, motivation, and emotional abilities. This framework, applied to different LLMs, uncovers diverse psychological profiles and highlights the influence of role assignments on model behaviors. The consistency observed across different models and settings emphasizes the potential of personalized LLMs and the infusion of human-like qualities into future AI systems.

"Game Ability" introduces GAMA, a benchmark provides a comprehensive evaluation of LLMs through the benchmark, focusing on aspects like robustness, reasoning strategies, generalizability, and comparative performance across different models. The studies reveal nuanced insights into how LLM performs under various conditions, including different game scenarios, temperature settings, and prompt constructions.The benchmarking effort not only advances our understanding of LLM behavior in controlled and dynamic environments but also sets a foundational framework for evaluating AI systems' decision-making and reasoning processes systematically.

Together, these studies not only highlight the evolving sophistication of LLMs in emulating human cognitive and behavioral aspects but also point to the imperative for continuous refinement in their development to tackle increasingly complex tasks. This convergence of psychological assessment and game-theoretical analysis in LLM research paves the way for deeper understanding and exploitation of AI's potential in the evolution towards more nuanced, and empathetic AI partners.

References

Saaket Agashe, Yue Fan, and Xin Eric Wang. Evaluating multi-agent coordination abilities in large language models. *arXiv preprint arXiv:2310.03903*, 2023.

Gati V Aher, Rosa I Arriaga, and Adam Tauman Kalai. Using large language models to simulate multiple humans and replicate human subject studies. In *International Conference on Machine Learning*, pp. 337–371. PMLR, 2023.

Elif Akata, Lion Schulz, Julian Coda-Forno, Seong Joon Oh, Matthias Bethge, and Eric Schulz. Playing repeated games with large language models. *arXiv preprint arXiv:2305.16867*, 2023.

Guilherme FCF Almeida, José Luiz Nunes, Neele Engelmann, Alex Wiegmann, and Marcelo de Araújo. Exploring the psychology of gpt-4's moral and legal reasoning. *arXiv preprint arXiv:2308.01264*, 2023.

Anne Anastasi and Susana Urbina. *Psychological testing*. Prentice Hall/Pearson Education, 1997.

Maryse Arcand, Robert-Paul Juster, Sonia J Lupien, and Marie-France Marin. Gender roles in relation to symptoms of anxiety and depression among students and workers. *Anxiety, Stress, & Coping*, 33(6):661–674, 2020.

Magda B Arnold. Emotion and personality. 1960.

Willem A Arrindell, Paul MG Emmelkamp, et al. Phobic dimensions: I. reliability and generalizability across samples, gender and nations: The fear survey schedule (fss-iii) and the fear questionnaire (fq). *Advances in Behaviour Research and Therapy*, 6(4):207–253, 1984.

W Brian Arthur. Inductive reasoning and bounded rationality. *The American economic review*, 84(2):406–411, 1994.

Daniel Ashlock and Garrison Greenwood. Generalized divide the dollar. In *2016 IEEE Congress on Evolutionary Computation (CEC)*, pp. 343–350. IEEE, 2016.

Carol J Auster and Susan C Ohm. Masculinity and femininity in contemporary american society: A reevaluation using the bem sex-role inventory. *Sex roles*, 43:499–528, 2000.

David Baidoo-Anu and Leticia Owusu Ansah. Education in the era of generative artificial intelligence (ai): Understanding the potential benefits of chatgpt in promoting teaching and learning. *Journal of AI*, 7(1):52–62, 2023.

Gerald V Barrett, James S Phillips, and Ralph A Alexander. Concurrent and predictive validity designs: A critical reanalysis. *Journal of Applied Psychology*, 66(1):1, 1981.

C Daniel Batson. 16 self-report ratings of empathic emotion. *Empathy and its development*, pp. 356, 1990.

Aaron T Beck, Robert A Steer, and Gregory Brown. Beck depression inventory–ii. *Psychological assessment*, 1996.

Sandra L Bem. The measurement of psychological androgyny. *Journal of consulting and clinical psychology*, 42(2): 155, 1974.

Sandra Lipsitz Bem. On the utility of alternative procedures for assessing psychological androgyny. *Journal of consulting and clinical psychology*, 45(2):196, 1977.

Chantal Berna, Tamara J Lang, Guy M Goodwin, and Emily A Holmes. Developing a measure of interpretation bias for depressed mood: An ambiguous scenarios test. *Personality and Individual Differences*, 51(3):349–354, 2011.

Marcel Binz and Eric Schulz. Turning large language models into cognitive models. *arXiv preprint arXiv:2306.03917*, 2023.

D Caroline Blanchard, April L Hynd, Karl A Minke, Tiffanie Minemoto, and Robert J Blanchard. Human defensive behaviors to threat scenarios show parallels to fear-and anxiety-related defense patterns of non-human mammals. *Neuroscience & Biobehavioral Reviews*, 25(7-8):761–770, 2001.

Bojana Bodroza, Bojana M Dinic, and Ljubisa Bojic. Personality testing of gpt-3: Limited temporal reliability, but highlighted social desirability of gpt-3's personality instruments results. *arXiv preprint arXiv:2306.04308*, 2023.

Nick Bostrom. *Superintelligence: Paths, Dangers, Strategies*. Oxford University Press, 2014.

Kelly A Brennan, Catherine L Clark, and Phillip R Shaver. Self-report measurement of adult attachment: An integrative overview. *Attachment theory and close relationships*, 1998.

Philip Brookins and Jason Matthew DeBacker. Playing games with gpt: What can we learn about a large language model from canonical strategic games? *Available at SSRN 4493398*, 2023.

Sébastien Bubeck, Varun Chandrasekaran, Ronen Eldan, Johannes Gehrke, Eric Horvitz, Ece Kamar, Peter Lee, Yin Tat Lee, Yuanzhi Li, Scott Lundberg, et al. Sparks of artificial general intelligence: Early experiments with gpt-4. *arXiv preprint arXiv:2303.12712*, 2023.

Arnold H Buss and Mark Perry. The aggression questionnaire. *Journal of personality and social psychology*, 63(3): 452, 1992.

Marco Cascella, Jonathan Montomoli, Valentina Bellini, and Elena Bignami. Evaluating the feasibility of chatgpt in healthcare: an analysis of multiple clinical and research scenarios. *Journal of Medical Systems*, 47(1):33, 2023.

Melody Manchi Chao, Riki Takeuchi, and Jiing-Lih Farh. Enhancing cultural intelligence: The roles of implicit culture beliefs and adjustment. *Personnel Psychology*, 70(1):257–292, 2017.

Jiangjie Chen, Siyu Yuan, Rong Ye, Bodhisattwa Prasad Majumder, and Kyle Richardson. Put your money where your mouth is: Evaluating strategic planning and execution of llm agents in an auction arena. *arXiv preprint arXiv:2310.05746*, 2023.

Myra Cheng, Esin Durmus, and Dan Jurafsky. Marked personas: Using natural language prompts to measure stereotypes in language models. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 1504–1532, Toronto, Canada, July 2023. Association for Computational Linguistics. URL https://aclanthology.org/2023.acl-long.84.

Lee Anna Clark and David Watson. Constructing validity: New developments in creating objective measuring instruments. *Psychological assessment*, 31(12):1412, 2019.

Julian Coda-Forno, Kristin Witte, Akshay K Jagadish, Marcel Binz, Zeynep Akata, and Eric Schulz. Inducing anxiety in large language models increases exploration and bias. *arXiv preprint arXiv:2304.11111*, 2023.

Ronald Jay Cohen, Mark E Swerdlik, and Suzanne M Phillips. *Psychological testing and assessment: An introduction to tests and measurement*. Mayfield Publishing Co., 1996.

Taya R Cohen, Scott T Wolf, Abigail T Panter, and Chester A Insko. Introducing the gasp scale: a new measure of guilt and shame proneness. *Journal of personality and social psychology*, 100(5):947, 2011.

Lee J Cronbach. Coefficient alpha and the internal structure of tests. *psychometrika*, 16(3):297–334, 1951.

Bruce N Cuthbert, Peter J Lang, Cyd Strauss, David Drobes, Christopher J Patrick, and Margaret M Bradley. The psychophysiology of anxiety disorder: Fear memory imagery. *Psychophysiology*, 40(3):407–422, 2003.

Sunhao Dai, Ninglu Shao, Haiyuan Zhao, Weijie Yu, Zihua Si, Chen Xu, Zhongxiang Sun, Xiao Zhang, and Jun Xu. Uncovering chatgpt's capabilities in recommender systems. *arXiv preprint arXiv:2305.02182*, 2023a.

Wei Dai, Jionghao Lin, Hua Jin, Tongguang Li, Yi-Shan Tsai, Dragan Gašević, and Guanliang Chen. Can large language models provide feedback to students? a case study on chatgpt. In *2023 IEEE International Conference on Advanced Learning Technologies (ICALT)*, pp. 323–325. IEEE, 2023b.

Richard J Davidson. Affective neuroscience and psychophysiology: Toward a synthesis. *Psychophysiology*, 40(5): 655–665, 2003.

Mark H Davis. Measuring individual differences in empathy: Evidence for a multidimensional approach. *Journal of personality and social psychology*, 44(1):113, 1983.

Joost CF de Winter. Can chatgpt pass high school exams on english language comprehension. *Researchgate. Preprint*, 2023.

Yinlin Deng, Chunqiu Steven Xia, Haoran Peng, Chenyuan Yang, and Lingming Zhang. Large language models are zero-shot fuzzers: Fuzzing deep-learning libraries via large language models. In *Proceedings of the 32nd ACM SIGSOFT International Symposium on Software Testing and Analysis*, pp. 423–435, 2023.

Aniket Deroy, Kripabandhu Ghosh, and Saptarshi Ghosh. How ready are pre-trained abstractive models and llms for legal case judgement summarization? *arXiv preprint arXiv:2306.01248*, 2023.

Ameet Deshpande, Vishvak Murahari, Tanmay Rajpurohit, Ashwin Kalyan, and Karthik Narasimhan. Toxicity in chatgpt: Analyzing persona-assigned language models. In Houda Bouamor, Juan Pino, and Kalika Bali (eds.), *Findings of the Association for Computational Linguistics: EMNLP 2023*, pp. 1236–1270, Singapore, December 2023a. Association for Computational Linguistics. doi: 10.18653/v1/2023.findings-emnlp.88. URL https://aclanthology.org/2023.findings-emnlp.88.

Ameet Deshpande, Vishvak Murahari, Tanmay Rajpurohit, Ashwin Kalyan, and Karthik Narasimhan. Toxicity in chatgpt: Analyzing persona-assigned language models. *arXiv preprint arXiv:2304.05335*, 2023b.

Joerg Dietz and Emmanuelle P Kleinlogel. Wage cuts and managers' empathy: How a positive emotion can contribute to positive organizational ethics in difficult times. *Journal of business ethics*, 119:461–472, 2014.

Danica Dillion, Niket Tandon, Yuling Gu, and Kurt Gray. Can ai language models replace human participants? *Trends in Cognitive Sciences*, 2023.

Jinhao Duan, Renming Zhang, James Diffenderfer, Bhavya Kailkhura, Lichao Sun, Elias Stengel-Eskin, Mohit Bansal, Tianlong Chen, and Kaidi Xu. Gtbench: Uncovering the strategic reasoning limitations of llms via game-theoretic evaluations. *arXiv preprint arXiv:2402.12348*, 2024.

Paul Ekman and Wallace V Friesen. Facial action coding system. *Environmental Psychology & Nonverbal Behavior*, 1978.

Sybil BG Eysenck, Hans J Eysenck, and Paul Barrett. A revised version of the psychoticism scale. *Personality and individual differences*, 6(1):21–29, 1985.

Caoyun Fan, Jindou Chen, Yaohui Jin, and Hao He. Can large language models serve as rational players in game theory? a systematic analysis. *arXiv preprint arXiv:2312.05488*, 2023a.

Zhiyu Fan, Xiang Gao, Martin Mirchev, Abhik Roychoudhury, and Shin Hwei Tan. Automated repair of programs from large language models. In *2023 IEEE/ACM 45th International Conference on Software Engineering (ICSE)*, pp. 1469–1481. IEEE, 2023b.

Nino Fijačko, Lucija Gosak, Gregor Štiglic, Christopher T Picard, and Matthew John Douma. Can chatgpt pass the life support exams without entering the american heart association course? *Resuscitation*, 185, 2023.

R Chris Fraley, Niels G Waller, and Kelly A Brennan. An item response theory analysis of self-report measures of adult attachment. *Journal of personality and social psychology*, 78(2):350, 2000.

R Chris Fraley, Marie E Heffernan, Amanda M Vicary, and Claudia Chloe Brumbaugh. The experiences in close relationships—relationship structures questionnaire: a method for assessing attachment orientations across relationships. *Psychological assessment*, 23(3):615, 2011.

Aidan Gilson, Conrad W Safranek, Thomas Huang, Vimig Socrates, Ling Chi, Richard Andrew Taylor, David Chartash, et al. How does chatgpt perform on the united states medical licensing examination? the implications of large language models for medical education and knowledge assessment. *JMIR Medical Education*, 9(1):e45312, 2023.

Salvatore Giorgi, Khoa Le Nguyen, Johannes C Eichstaedt, Margaret L Kern, David B Yaden, Michal Kosinski, Martin EP Seligman, Lyle H Ungar, H Andrew Schwartz, and Gregory Park. Regional personality assessment through social media language. *Journal of personality*, 90(3):405–425, 2022.

Natalie S Glance and Bernardo A Huberman. The dynamics of social dilemmas. *Scientific American*, 270(3):76–81, 1994.

Robert E Goodin. *The theory of institutional design*. Cambridge University Press, 1998.

Neel Guha, Julian Nyarko, Daniel E Ho, Christopher Re, Adam Chilton, Aditya Narayana, Alex Chohlas-Wood, Austin Peters, Brandon Waldon, Daniel Rockmore, et al. Legalbench: A collaboratively built benchmark for measuring legal reasoning in large language models. In *Thirty-seventh Conference on Neural Information Processing Systems Datasets and Benchmarks Track*, 2023.

Tanya Guitard, Stéphane Bouchard, Claude Bélanger, and Maxine Berthiaume. Exposure to a standardized catastrophic scenario in virtual reality or a personalized scenario in imagination for generalized anxiety disorder. *Journal of clinical Medicine*, 8(3):309, 2019.

Fulin Guo. Gpt agents in game theory experiments. *arXiv preprint arXiv:2305.05516*, 2023.

Jiaxian Guo, Bo Yang, Paul Yoo, Bill Yuchen Lin, Yusuke Iwasawa, and Yutaka Matsuo. Suspicion-agent: Playing imperfect information games with theory of mind aware gpt-4. *arXiv preprint arXiv:2309.17277*, 2023.

Akshat Gupta, Xiaoyang Song, and Gopala Anumanchipalli. Investigating the applicability of self-assessment tests for personality measurement of large language models. *arXiv preprint arXiv:2309.08163*, 2023.

Louis Guttman. A basis for analyzing test-retest reliability. *Psychometrika*, 10(4):255–282, 1945.

Thilo Hagendorff. Machine psychology: Investigating emergent capabilities and behavior in large language models using psychological methods. *arXiv preprint arXiv:2303.13988*, 2023.

Jacqueline Harding, William D'Alessandro, N. G. Laskowski, and Robert Long. Ai language models cannot replace human research participants. *AI & SOCIETY*, 2023.

Neil Harrington. The frustration discomfort scale: Development and psychometric properties. *Clinical Psychology & Psychotherapy: An International Journal of Theory & Practice*, 12(5):374–387, 2005.

Julie D Henry and John R Crawford. The short-form version of the depression anxiety stress scales (dass-21): Construct validity and normative data in a large non-clinical sample. *British journal of clinical psychology*, 44(2):227–239, 2005.

Babak Heydari and Nunzio Lorè. Strategic behavior of large language models: Game structure vs. contextual framing. *Contextual Framing (September 10, 2023)*, 2023.

John J Horton. Large language models as simulated economic agents: What can we learn from homo silicus? Technical report, National Bureau of Economic Research, 2023.

Jen-tse Huang, Man Ho Lam, Eric John Li, Shujie Ren, Wenxuan Wang, Wenxiang Jiao, Zhaopeng Tu, and Michael R Lyu. Emotionally numb or empathetic? evaluating how llms feel using emotionbench. *arXiv preprint arXiv:2308.03656*, 2023a.

Jen-tse Huang, Wenxuan Wang, Man Ho Lam, Eric John Li, Wenxiang Jiao, and Michael R Lyu. Chatgpt an enfj, bard an istj: Empirical study on personalities of large language models. *arXiv preprint arXiv:2305.19926*, 2023b.

Jen-tse Huang, Wenxuan Wang, Eric John Li, Man Ho Lam, Shujie Ren, Youliang Yuan, Wenxiang Jiao, Zhaopeng Tu, and Michael R Lyu. Who is chatgpt? benchmarking llms' psychological portrayal using psychobench. In *Proceedings of the Twelfth International Conference on Learning Representations*, 2024.

Yufei Huang and Deyi Xiong. Cbbq: A chinese bias benchmark dataset curated with human-ai collaboration for large language models. *arXiv preprint arXiv:2306.16244*, 2023.

Bernardo A. Huberman. *The Ecology of Computation*. North-Holland, 1988.

Guangyuan Jiang, Manjie Xu, Song-Chun Zhu, Wenjuan Han, Chi Zhang, and Yixin Zhu. Evaluating and inducing personality in pre-trained language models. *arXiv preprint arXiv:2206.07550*, 2022.

Hang Jiang, Xiajie Zhang, Xubo Cao, Jad Kabbara, and Deb Roy. Personallm: Investigating the ability of gpt-3.5 to express personality traits and gender differences. *arXiv preprint arXiv:2305.02547*, 2023.

Wenxiang Jiao, Wenxuan Wang, Jen-tse Huang, Xing Wang, and Zhaopeng Tu. Is chatgpt a good translator? a preliminary study. *arXiv preprint arXiv:2301.08745*, 2023.

Oliver P John, Sanjay Srivastava, et al. The big-five trait taxonomy: History, measurement, and theoretical perspectives. *Handbook of personality: theory and research*, 1999.

Douglas Johnson, Rachel Goodman, J Patrinely, Cosby Stone, Eli Zimmerman, Rebecca Donald, Sam Chang, Sean Berkowitz, Avni Finn, Eiman Jahangir, et al. Assessing the accuracy and reliability of ai-generated medical responses: an evaluation of the chat-gpt model. *Research square*, 2023.

Peter K Jonason and Gregory D Webster. The dirty dozen: a concise measure of the dark triad. *Psychological assessment*, 22(2):420, 2010.

Saketh Reddy Karra, Son Nguyen, and Theja Tulabandhula. Ai personification: Estimating the personality of language models. *arXiv preprint arXiv:2204.12000*, 2022a.

Saketh Reddy Karra, Son The Nguyen, and Theja Tulabandhula. Estimating the personality of white-box language models. *arXiv preprint arXiv:2204.12000*, 2022b.

Matthew C Keller and Randolph M Nesse. Is low mood an adaptation? evidence for subtypes with symptoms that match precipitants. *Journal of affective disorders*, 86(1):27–35, 2005.

D Marc Kilgour and Steven J Brams. The truel. *Mathematics Magazine*, 70(5):315–326, 1997.

D Mark Kilgour. The sequential truel. *International Journal of Game Theory*, 4:151–174, 1975.

Takeshi Kojima, Shixiang Shane Gu, Machel Reid, Yutaka Matsuo, and Yusuke Iwasawa. Large language models are zero-shot reasoners. *Advances in neural information processing systems*, 35:22199–22213, 2022.

Aobo Kong, Shiwan Zhao, Hao Chen, Qicheng Li, Yong Qin, Ruiqi Sun, and Xin Zhou. Better zero-shot reasoning with role-play prompting. *arXiv preprint arXiv:2308.07702*, 2023.

Michal Kosinski. Theory of mind might have spontaneously emerged in large language models. *arXiv preprint arXiv:2302.02083*, 2023.

Samuel E Krug and Raymond W Kulhavy. Personality differences across regions of the united states. *The Journal of social psychology*, 91(1):73–79, 1973.

Tiffany H Kung, Morgan Cheatham, Arielle Medenilla, Czarina Sillos, Lorie De Leon, Camille Elepaño, Maria Madriaga, Rimel Aggabao, Giezel Diaz-Candido, James Maningo, et al. Performance of chatgpt on usmle: Potential for ai-assisted medical education using large language models. *PLoS digital health*, 2(2):e0000198, 2023.

Tom R Kupfer, Morgan J Sidari, Brendan P Zietsch, Patrick Jern, Joshua M Tybur, and Laura W Wesseldijk. Why are some people more jealous than others? genetic and environmental factors. *Evolution and Human Behavior*, 43(1): 26–33, 2022.

Viet Lai, Nghia Ngo, Amir Pouran Ben Veyseh, Hieu Man, Franck Dernoncourt, Trung Bui, and Thien Nguyen. ChatGPT beyond English: Towards a comprehensive evaluation of large language models in multilingual learning. In Houda Bouamor, Juan Pino, and Kalika Bali (eds.), *Findings of the Association for Computational Linguistics: EMNLP 2023*, pp. 13171–13189, Singapore, December 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.findings-emnlp.878. URL https://aclanthology.org/2023.findings-emnlp.878.

Yihuai Lan, Zhiqiang Hu, Lei Wang, Yang Wang, Deheng Ye, Peilin Zhao, Ee-Peng Lim, Hui Xiong, and Hao Wang. Llm-based agent society investigation: Collaboration and confrontation in avalon gameplay. *arXiv preprint arXiv:2310.14985*, 2023.

Pier Luca Lanzi and Daniele Loiacono. Chatgpt and other large language models as evolutionary engines for online interactive collaborative game design. *arXiv preprint arXiv:2303.02155*, 2023.

Kenneth S Law, Chi-Sum Wong, and Lynda J Song. The construct and criterion validity of emotional intelligence and its potential utility for management studies. *Journal of applied Psychology*, 89(3):483, 2004.

Richard S Lazarus. *Emotion and adaptation*. Oxford University Press, 1991.

Mark R Leary. A brief version of the fear of negative evaluation scale. *Personality and social psychology bulletin*, 9 (3):371–375, 1983.

Alain Ledoux. Concours résultats complets. les victimes se sont plu à jouer le 14 d'atout. *Jeux & Stratégie*, 2(10): 10–11, 1981.

Choonghyoung Lee, Jahyun Song, and Bill Ryan. When employees feel envy: The role of psychological capital. *International Journal of Hospitality Management*, 105:103251, 2022.

Cheng Li, Jindong Wang, Kaijie Zhu, Yixuan Zhang, Wenxin Hou, Jianxun Lian, and Xing Xie. Emotionprompt: Leveraging psychology for large language models enhancement via emotional stimulus. *arXiv preprint arXiv:2307.11760*, 2023a.

Jiatong Li, Rui Li, and Qi Liu. Beyond static datasets: A deep interaction approach to llm evaluation. *arXiv preprint arXiv:2309.04369*, 2023b.

Xingxuan Li, Yutong Li, Shafiq Joty, Linlin Liu, Fei Huang, Lin Qiu, and Lidong Bing. Does gpt-3 demonstrate psychopathy? evaluating large language models from a psychological perspective. *arXiv preprint arXiv:2212.10529*, 2022a.

Xingxuan Li, Yutong Li, Linlin Liu, Lidong Bing, and Shafiq Joty. Is gpt-3 a psychopath? evaluating large language models from a psychological perspective. *arXiv preprint arXiv:2212.10529*, 2022b.

Tian Liang, Zhiwei He, Jen-tes Huang, Wenxuan Wang, Wenxiang Jiao, Rui Wang, Yujiu Yang, Zhaopeng Tu, Shuming Shi, and Xing Wang. Leveraging word guessing games to assess the intelligence of large language models. *arXiv preprint arXiv:2310.20499*, 2023a.

Tian Liang, Zhiwei He, Wenxiang Jiao, Xing Wang, Yan Wang, Rui Wang, Yujiu Yang, Zhaopeng Tu, and Shuming Shi. Encouraging divergent thinking in large language models through multi-agent debate. *arXiv preprint arXiv:2305.19118*, 2023b.

Stephanie Lin, Jacob Hilton, and Owain Evans. Truthfulqa: Measuring how models mimic human falsehoods. *arXiv preprint arXiv:2109.07958*, 2021.

Hanmeng Liu, Ruoxi Ning, Zhiyang Teng, Jian Liu, Qiji Zhou, and Yue Zhang. Evaluating the logical reasoning ability of chatgpt and gpt-4. *arXiv preprint arXiv:2304.03439*, 2023a.

Yi Liu, Gelei Deng, Yuekang Li, Kailong Wang, Tianwei Zhang, Yepang Liu, Haoyu Wang, Yan Zheng, and Yang Liu. Prompt injection attack against llm-integrated applications. *arXiv preprint arXiv:2306.05499*, 2023b.

Tobias Luck and Claudia Luck-Sikorski. The wide variety of reasons for feeling guilty in adults: findings from a large cross-sectional web-based survey. *BMC psychology*, 10(1):1–20, 2022.

Romualdas Malinauskas, Audrone Dumciene, Saule Sipaviciene, and Vilija Malinauskiene. Relationship between emotional intelligence and health behaviours among university students: The predictive and moderating role of gender. *BioMed research international*, 2018, 2018.

Shaoguang Mao, Yuzhe Cai, Yan Xia, Wenshan Wu, Xun Wang, Fengyi Wang, Tao Ge, and Furu Wei. Alympics: Language agents meet game theory. *arXiv preprint arXiv:2311.03220*, 2023.

Ryan C Martin and Eric R Dahlen. The angry cognitions scale: A new inventory for assessing cognitions in anger. *Journal of Rational-Emotive & Cognitive-Behavior Therapy*, 25:155–173, 2007.

John D Mayer, Peter Salovey, and David R Caruso. Mayer-salovey-caruso emotional intelligence test (msceit) users manual. 2002.

R Preston McAfee and John McMillan. Auctions and bidding. *Journal of economic literature*, 25(2):699–738, 1987.

Samuel Messick. Test validity: A matter of consequence. *Social Indicators Research*, 45:35–44, 1998.

Marilù Miotto, Nicola Rossberg, and Bennett Kleinberg. Who is GPT-3? an exploration of personality, values and demographics. In *Proceedings of the Fifth Workshop on Natural Language Processing and Computational Social Science (NLP+CSS)*, pp. 218–227, Abu Dhabi, UAE, November 2022. Association for Computational Linguistics. URL https://aclanthology.org/2022.nlpcss-1.24.

Agnes Moors, Phoebe C Ellsworth, Klaus R Scherer, and Nico H Frijda. Appraisal theories of emotion: State of the art and future development. *Emotion Review*, 5(2):119–124, 2013.

Dor Muhlgay, Ori Ram, Inbal Magar, Yoav Levine, Nir Ratner, Yonatan Belinkov, Omri Abend, Kevin Leyton-Brown, Amnon Shashua, and Yoav Shoham. Generating benchmarks for factuality evaluation of language models. *arXiv preprint arXiv:2307.06908*, 2023.

Isabel Briggs Myers. *The Myers-Briggs Type Indicator: Manual (1962)*. Consulting Psychologists Press, 1962.

Roger B Myerson. *Game theory*. Harvard university press, 2013.

Rosemarie Nagel. Unraveling in guessing games: An experimental study. *The American economic review*, 85(5): 1313–1326, 1995.

Seishu Nakagawa, Hikaru Takeuchi, Yasuyuki Taki, Rui Nouchi, Atsushi Sekiguchi, Yuka Kotozaki, Carlos Makoto Miyauchi, Kunio Iizuka, Ryoichi Yokoyama, Takamitsu Shinada, et al. Comprehensive neural networks for guilty feelings in young adults. *Neuroimage*, 105:248–256, 2015.

John F Nash. Equilibrium points in n-person games. *Proceedings of the national academy of sciences*, 36(1):48–49, 1950.

John F Nash. Non-cooperative games. *Annals of Mathematics*, 54(2):286–295, 1951.

John J Nay, David Karamardian, Sarah B Lawsky, Wenting Tao, Meghana Bhat, Raghav Jain, Aaron Travis Lee, Jonathan H Choi, and Jungo Kasai. Large language models as tax attorneys: A case study in legal capabilities emergence. *arXiv preprint arXiv:2306.07075*, 2023.

Kok-Mun Ng, Chuang Wang, Carlos P Zalaquett, and Nancy Bodenhorn. A confirmatory factor analysis of the wong and law emotional intelligence scale in a sample of international college students. *International Journal for the Advancement of Counselling*, 29:173–185, 2007.

Jum C. Nunnally and Ira H. Bernstein. *Psychometric Theory (3rd edition)*. McGraw-Hill, 1994.

Aidan O'Gara. Hoodwinked: Deception and cooperation in a text-based game for language models. *arXiv preprint arXiv:2308.01404*, 2023.

OpenAI. Gpt-4 technical report. *arXiv preprint arXiv:2303.08774*, 2023.

Joowon Park, Sachin Banker, Tamara Masters, and Grace Yu-Buck. Person vs. purchase comparison: how material and experiential purchases evoke consumption-related envy in others. *Journal of Business Research*, 165:114014, 2023a.

Peter S Park, Philipp Schoenegger, and Chongyang Zhu. Artificial intelligence in psychology research. *arXiv preprint arXiv:2302.07267*, 2023b.

Joseph Persky. Retrospectives: The ethology of homo economicus. *Journal of Economic Perspectives*, 9(2):221–231, 1995.

Konstantine V Petrides and Adrian Furnham. On the dimensional structure of emotional intelligence. *Personality and individual differences*, 29(2):313–320, 2000.

Susan M Pfeiffer and Paul TP Wong. Multidimensional jealousy. *Journal of social and personal relationships*, 6(2): 181–196, 1989.

Steve Phelps and Yvan I Russell. Investigating emergent goal-like behaviour in large language models using experimental economics. *arXiv preprint arXiv:2305.07970*, 2023.

Sundar Pichai and Demis Hassabis. Introducing gemini: our largest and most capable ai model. *Google Blog Dec 06 2023*, 2023. URL `https://blog.google/technology/ai/google-gemini-ai/`.

Hok-Ko Pong and Paul Lam. The effect of service learning on the development of trait emotional intelligence and adversity quotient in youths: An experimental study. *International Journal of Environmental Research and Public Health*, 20(6):4677, 2023.

Dan Qiao, Chenfei Wu, Yaobo Liang, Juntao Li, and Nan Duan. Gameeval: Evaluating llms on conversational games. *arXiv preprint arXiv:2308.10032*, 2023.

Chengwei Qin, Aston Zhang, Zhuosheng Zhang, Jiaao Chen, Michihiro Yasunaga, and Diyi Yang. Is chatgpt a general-purpose natural language processing task solver? *arXiv preprint arXiv:2302.06476*, 2023.

Haocong Rao, Cyril Leung, and Chunyan Miao. Can chatgpt assess human personalities? a general evaluation framework. *arXiv preprint arXiv:2303.01248*, 2023.

Peter J Rentfrow, Markus Jokela, and Michael E Lamb. Regional personality differences in great britain. *PloS one*, 10 (3):e0122245, 2015.

Peter Romero, Stephen Fitz, and Teruo Nakatsuma. Do gpt language models suffer from split personality disorder? the advent of substrate-free psychometrics. *Research Square preprint*, 2023. doi: 10.21203/rs.3.rs-2717108/v1.

Ira J Roseman and Craig A Smith. Appraisal theory. *Appraisal processes in emotion: Theory, methods, research*, pp. 3–19, 2001.

Ariel Rubinstein. Instinctive and cognitive reasoning: A study of response times. *The Economic Journal*, 117(523): 1243–1259, 2007.

Jérôme Rutinowski, Sven Franke, Jan Endendyk, Ina Dormuth, and Markus Pauly. The self-perception and political biases of chatgpt. *arXiv preprint arXiv:2304.07333*, 2023.

John Sabini, Michael Siepmann, Julia Stein, and Marcia Meyerowitz. Who is embarrassed by what? *Cognition & Emotion*, 14(2):213–240, 2000.

John Sabini, Brian Garvey, and Amanda L Hall. Shame and embarrassment revisited. *Personality and Social Psychology Bulletin*, 27(1):104–117, 2001.

Mustafa Safdari, Greg Serapio-García, Clément Crepy, Stephen Fitz, Peter Romero, Luning Sun, Marwa Abdulhai, Aleksandra Faust, and Maja Matarić. Personality traits in large language models. *arXiv preprint arXiv:2307.00184*, 2023.

Donald H Saklofske, Elizabeth J Austin, and Paul S Minski. Factor structure and validity of a trait emotional intelligence measure. *Personality and Individual differences*, 34(4):707–721, 2003.

Paul A Samuelson. The pure theory of public expenditure. *The review of economics and statistics*, 36(4):387–389, 1954.

Shibani Santurkar, Esin Durmus, Faisal Ladhak, Cinoo Lee, Percy Liang, and Tatsunori Hashimoto. Whose opinions do language models reflect? In *International Conference on Machine Learning*, pp. 29971–30004. PMLR, 2023.

Kristina Schaaff, Caroline Reinig, and Tim Schlippe. Exploring chatgpt's empathic abilities. *arXiv preprint arXiv:2308.03527*, 2023.

Michael F Scheier and Charles S Carver. Optimism, coping, and health: assessment and implications of generalized outcome expectancies. *Health psychology*, 4(3):219, 1985.

Michael F Scheier, Charles S Carver, and Michael W Bridges. Distinguishing optimism from neuroticism (and trait anxiety, self-mastery, and self-esteem): a reevaluation of the life orientation test. *Journal of personality and social psychology*, 67(6):1063, 1994.

Klaus R Scherer. Appraisal theory. 1999.

Nino Scherrer, Claudia Shi, Amir Feder, and David M Blei. Evaluating the moral beliefs encoded in llms. *arXiv preprint arXiv:2307.14324*, 2023.

Urte Scholz, Benicio Gutiérrez Doña, Shonali Sud, and Ralf Schwarzer. Is general self-efficacy a universal construct? psychometric findings from 25 countries. *European journal of psychological assessment*, 18(3):242, 2002.

Nicola S Schutte, John M Malouff, Lena E Hall, Donald J Haggerty, Joan T Cooper, Charles J Golden, and Liane Dornheim. Development and validation of a measure of emotional intelligence. *Personality and individual differences*, 25(2):167–177, 1998.

Ralf Schwarzer and Matthias Jerusalem. Generalized self-efficacy scale. *J. Weinman, S. Wright, & M. Johnston, Measures in health psychology: A user's portfolio. Causal and control beliefs*, 35:37, 1995.

Yunfan Shao, Linyang Li, Junqi Dai, and Xipeng Qiu. Character-LLM: A trainable agent for role-playing. In Houda Bouamor, Juan Pino, and Kalika Bali (eds.), *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pp. 13153–13187, Singapore, December 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.emnlp-main.814. URL https://aclanthology.org/2023.emnlp-main.814.

Lloyd S Shapley and Martin Shubik. Pure competition, coalitional power, and fair division. *International Economic Review*, 10(3):337–362, 1969.

Kotaro Shoji, Jinni A Harrigan, Stanley B Woll, and Steven A Miller. Interactions among situations, neuroticism, and appraisals in coping strategy choice. *Personality and Individual Differences*, 48(3):270–276, 2010.

Bangzhao Shu, Lechen Zhang, Minje Choi, Lavinia Dunagan, Dallas Card, and David Jurgens. You don't need a personality test to know these models are unreliable: Assessing the reliability of large language models on psychometric instruments. *arXiv preprint arXiv:2311.09718*, 2023.

Kate Simpson, Dawn Adams, Kathryn Ambrose, and Deb Keen. "my cheeks get red and my brain gets scared": A computer assisted interview to explore experiences of anxiety in young children on the autism spectrum. *Research in Developmental Disabilities*, 113:103940, 2021.

Xiaoyang Song, Akshat Gupta, Kiyan Mohebbizadeh, Shujie Hu, and Anant Singh. Have large language models developed a personality?: Applicability of self-assessment tests in measuring personality in llms. *arXiv preprint arXiv:2305.14693*, 2023.

Sanjay Srivastava, Oliver P John, Samuel D Gosling, and Jeff Potter. Development of personality in early and middle adulthood: Set like plaster or persistent change? *Journal of personality and social psychology*, 84(5):1041, 2003.

Simon Stepputtis, Joseph Campbell, Yaqi Xie, Zhengyang Qi, Wenxin Sharon Zhang, Ruiyi Wang, Sanketh Rangreji, Michael Lewis, and Katia Sycara. Long-horizon dialogue understanding for role identification in the game of avalon with large language models. *arXiv preprint arXiv:2311.05720*, 2023.

Ian Stewart. A puzzle for pirates. *Scientific American*, 280(5):98–99, 1999.

Rong Su, Louis Tay, Hsin-Ya Liao, Qi Zhang, and James Rounds. Toward a dimensional model of vocational interests. *Journal of Applied Psychology*, 104(5):690, 2019.

Mark JM Sullman. Anger amongst new zealand drivers. *Transportation Research Part F: Traffic Psychology and Behaviour*, 9(3):173–184, 2006.

Nigar M Shafiq Surameery and Mohammed Y Shakor. Use chat gpt to solve programming bugs. *International Journal of Information Technology & Computer Engineering (IJITC) ISSN: 2455-5290*, 3(01):17–22, 2023.

Ala N. Tak and Jonathan Gratch. Is gpt a computational model of emotion? detailed analysis. *arXiv preprint arXiv:2307.13779*, 2023.

Yiming Tan, Dehai Min, Yu Li, Wenbo Li, Nan Hu, Yongrui Chen, and Guilin Qi. Evaluation of chatgpt as a question answering system for answering complex questions. *arXiv preprint arXiv:2303.07992*, 2023.

Thomas Li-Ping Tang, Toto Sutarso, Adebowale Akande, Michael W Allen, Abdulgawi Salim Alzubaidi, Mahfooz A Ansari, Fernando Arias-Galicia, Mark G Borg, Luigina Canova, Brigitte Charles-Pauvers, et al. The love of money and pay level satisfaction: Measurement and functional equivalence in 29 geopolitical entities around the world. *Management and Organization Review*, 2(3):423–452, 2006.

Qing Tian and Jennifer L Robertson. How and when does perceived csr affect employees' engagement in voluntary pro-environmental behavior? *Journal of Business Ethics*, 155:399–412, 2019.

Michael Tomasello. *The Cultural Origins of Human Cognition*. Harvard University Press, 1999.

Bertil Törestad. What is anger provoking? a psychophysical study of perceived causes of anger. *Aggressive Behavior*, 16(1):9–26, 1990.

Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. Llama 2: Open foundation and fine-tuned chat models. *arXiv preprint arXiv:2307.09288*, 2023.

Chen Feng Tsai, Xiaochen Zhou, Sierra S Liu, Jing Li, Mo Yu, and Hongyuan Mei. Can large language models play text games well? current state-of-the-art and open questions. *arXiv preprint arXiv:2304.02868*, 2023.

William Vickrey. Counterspeculation, auctions, and competitive sealed tenders. *The Journal of finance*, 16(1):8–37, 1961.

David Walsh, Gerry McCartney, Sarah McCullough, Marjon van der Pol, Duncan Buchanan, and Russell Jones. Always looking on the bright side of life? exploring optimism and health in three uk post-industrial urban settings. *Journal of Public Health*, 37(3):389–397, 2015.

Yuxuan Wan, Wenxuan Wang, Pinjia He, Jiazhen Gu, Haonan Bai, and Michael Lyu. Biasasker: Measuring the bias in conversational ai system. In *The ACM Joint European Software Engineering Conference and Symposium on the Foundations of Software Engineering (ESEC/FSE)*. ACM, 2023.

Shenzhi Wang, Chang Liu, Zilong Zheng, Siyuan Qi, Shuo Chen, Qisen Yang, Andrew Zhao, Chaofei Wang, Shiji Song, and Gao Huang. Avalon's game of thoughts: Battle against deception through recursive contemplation. *arXiv preprint arXiv:2310.01320*, 2023a.

Wenxuan Wang, Zhaopeng Tu, Chang Chen, Youliang Yuan, Jen-tse Huang, Wenxiang Jiao, and Michael R Lyu. All languages matter: On the multilingual safety of large language models. *arXiv preprint arXiv:2310.00905*, 2023b.

Xintao Wang, Yaying Fei, Ziang Leng, and Cheng Li. Does role-playing chatbots capture the character personalities? assessing personality traits for role-playing chatbots. *arXiv preprint arXiv:2310.17976*, 2023c.

Xuena Wang, Xueting Li, Zi Yin, Yue Wu, and Liu Jia. Emotional intelligence of large language models. *arXiv preprint arXiv:2307.09042*, 2023d.

Zekun Moore Wang, Zhongyuan Peng, Haoran Que, Jiaheng Liu, Wangchunshu Zhou, Yuhan Wu, Hongcheng Guo, Ruitong Gan, Zehao Ni, Man Zhang, et al. Rolellm: Benchmarking, eliciting, and enhancing role-playing abilities of large language models. *arXiv preprint arXiv:2310.00746*, 2023e.

David Watson, Lee Anna Clark, and Auke Tellegen. Development and validation of brief measures of positive and negative affect: the panas scales. *Journal of personality and social psychology*, 54(6):1063, 1988.

David Wechsler. Wechsler adult intelligence scale–third edition. *Frontiers in Psychology*, 1997.

David Wechsler. Wechsler adult intelligence scale–fourth edition. *Archives of Clinical Neuropsychology*, 2008.

Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Fei Xia, Ed Chi, Quoc V Le, Denny Zhou, et al. Chain-of-thought prompting elicits reasoning in large language models. *Advances in Neural Information Processing Systems*, 35:24824–24837, 2022.

Tianwen Wei, Jian Luan, Wei Liu, Shuang Dong, and Bin Wang. Cmath: Can your language model pass chinese elementary school math test? *arXiv preprint arXiv:2306.16636*, 2023.

Chi-Sum Wong and Kenneth S Law. The effects of leader and follower emotional intelligence on performance and attitude: An exploratory study. *The leadership quarterly*, 13(3):243–274, 2002.

Jared Wong and Jin Kim. Chatgpt is more likely to be perceived as male than female. *arXiv preprint arXiv:2305.12564*, 2023.

Haoran Wu, Wenxuan Wang, Yuxuan Wan, Wenxiang Jiao, and Michael Lyu. Chatgpt or grammarly? evaluating chatgpt on grammatical error correction benchmark. *arXiv preprint arXiv:2303.13648*, 2023a.

Yue Wu, Xuan Tang, Tom M Mitchell, and Yuanzhi Li. Smartplay: A benchmark for llms as intelligent agents. *arXiv preprint arXiv:2310.01557*, 2023b.

Fangzhi Xu, Qika Lin, Jiawei Han, Tianzhe Zhao, Jun Liu, and Erik Cambria. Are large language models really good logical reasoners? a comprehensive evaluation from deductive, inductive and abductive views. *arXiv preprint arXiv:2306.09841*, 2023a.

Lin Xu, Zhiyuan Hu, Daquan Zhou, Hongyu Ren, Zhen Dong, Kurt Keutzer, and Jiashi Feng. Magic: Investigation of large language model powered multi-agent in cognition, adaptability, rationality and collaboration. *arXiv e-prints*, pp. arXiv–2311, 2023b.

Yuzhuang Xu, Shuo Wang, Peng Li, Fuwen Luo, Xiaolong Wang, Weidong Liu, and Yang Liu. Exploring large language models for communication games: An empirical study on werewolf. *arXiv preprint arXiv:2309.04658*, 2023c.

Zelai Xu, Chao Yu, Fei Fang, Yu Wang, and Yi Wu. Language agents with reinforcement learning for strategic play in the werewolf game. *arXiv preprint arXiv:2310.18940*, 2023d.

Youliang Yuan, Wenxiang Jiao, Wenxuan Wang, Jen-tse Huang, Pinjia He, Shuming Shi, and Zhaopeng Tu. Gpt-4 is too smart to be safe: Stealthy chat with llms via cipher. *arXiv preprint arXiv:2308.06463*, 2023a.

Zheng Yuan, Hongyi Yuan, Chuanqi Tan, Wei Wang, and Songfang Huang. How well do large language models perform in arithmetic tasks? *arXiv preprint arXiv:2304.02015*, 2023b.

Zihao Zhao, Eric Wallace, Shi Feng, Dan Klein, and Sameer Singh. Calibrate before use: Improving few-shot performance of language models. In *International Conference on Machine Learning*, pp. 12697–12706. PMLR, 2021.

Zexuan Zhong, Zhengxuan Wu, Christopher D Manning, Christopher Potts, and Danqi Chen. Mquake: Assessing knowledge editing in language models via multi-hop questions. *arXiv preprint arXiv:2305.14795*, 2023.

Kaijie Zhu, Jindong Wang, Jiaheng Zhou, Zichen Wang, Hao Chen, Yidong Wang, Linyi Yang, Wei Ye, Neil Zhenqiang Gong, Yue Zhang, et al. Promptbench: Towards evaluating the robustness of large language models on adversarial prompts. *arXiv preprint arXiv:2306.04528*, 2023a.

Yutao Zhu, Huaying Yuan, Shuting Wang, Jiongnan Liu, Wenhan Liu, Chenlong Deng, Zhicheng Dou, and Ji-Rong Wen. Large language models for information retrieval: A survey. *arXiv preprint arXiv:2308.07107*, 2023b.

Terry Yue Zhuo, Yujin Huang, Chunyang Chen, and Zhenchang Xing. Exploring ai ethics of chatgpt: A diagnostic analysis. *arXiv preprint arXiv:2301.12867*, 2023.

Part VII

Appendix

A Reliability Tests on Other LLMs

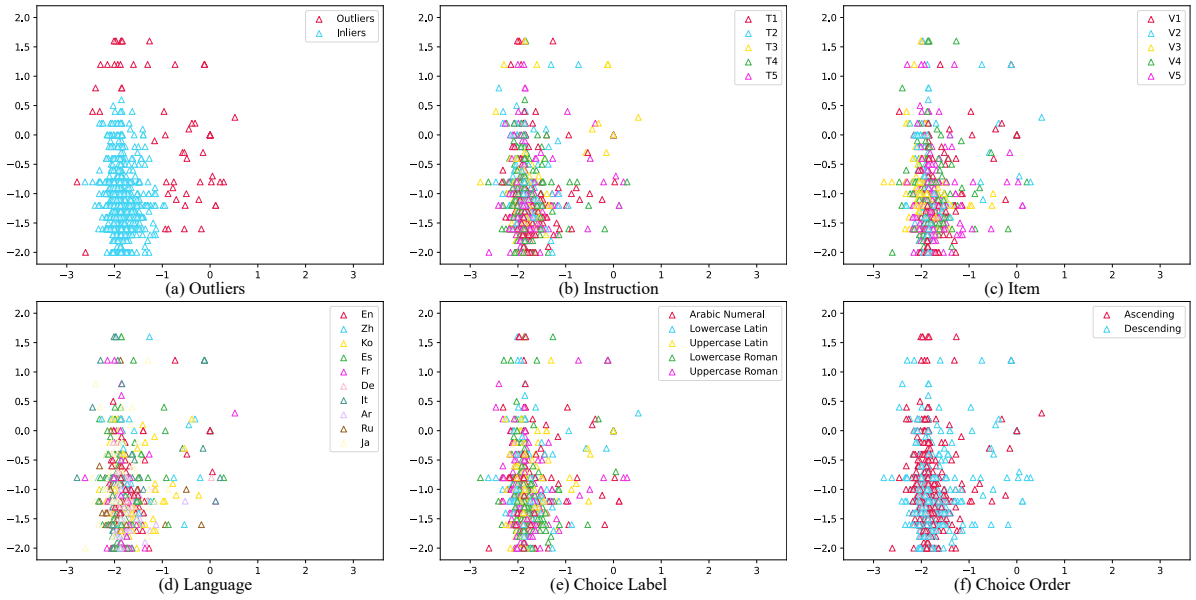

Figure 22: Visualization of all data points produced by `gpt-4` regarding different factors, marked in distinct colors.

We also explore the reliability of different LLMs on the BFI, taking into account their variations in training datasets and instruction tuning methodologies. We extend our analysis to include OpenAI's `gpt-4` (OpenAI, 2023) and Google's `Gemini-Pro` (Pichai & Hassabis, 2023), running on the same 2,500 profiles as those applied to `gpt-3.5-turbo`. Fig. 22 and Fig. 23 illustrate the data points generated from `gpt-4` and `Gemini`, respectively. Consistent with our previous experiments on `gpt-3.5-turbo`, we utilize DBSCAN parameters of `eps` $= 0.3$ and `minPt` $= 20$. The outlier rates for `gpt-4` and `Gemini-Pro` are approximately 4.1% and 2.4%, respectively. Our findings indicate that: (1) The model responses are not uniformly distributed across the BFI space, suggesting a significant level of reliability across all examined LLMs. (2) Each model exhibits a unique personality profile. `gpt-4`'s personality significantly diverges from that of `gpt-3.5-turbo`, whereas `Gemini-Pro` displays a personality more akin to `gpt-3.5-turbo`. For clarity, we present the personality distribution of the three models in Fig. 24.

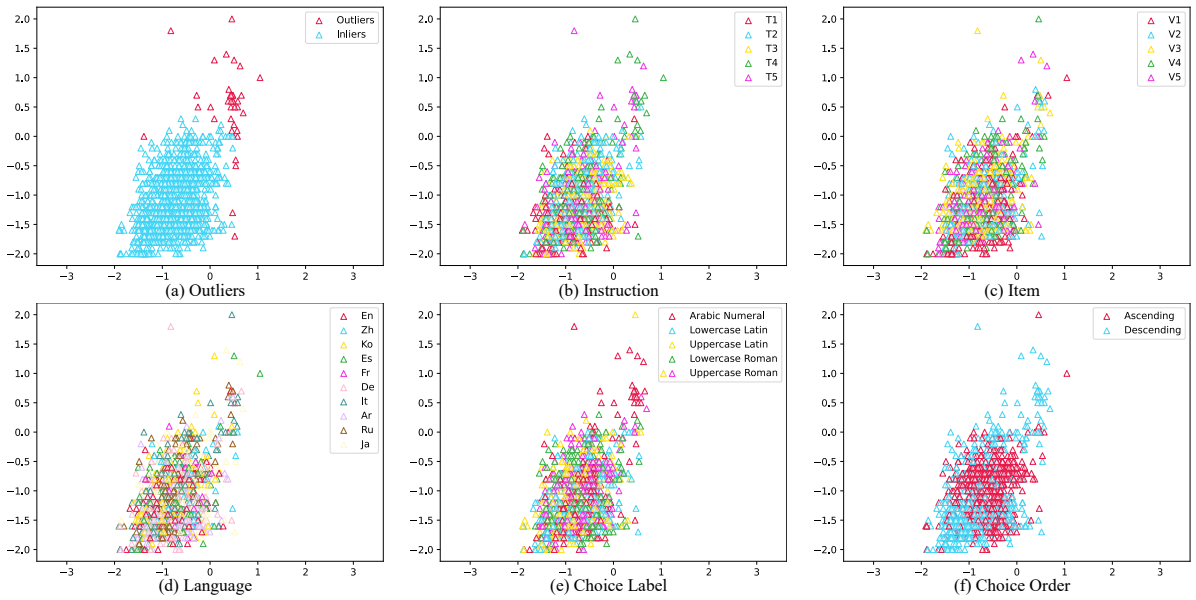

Figure 23: Visualization of all data points produced by `Gemini` regarding different factors, marked in distinct colors.

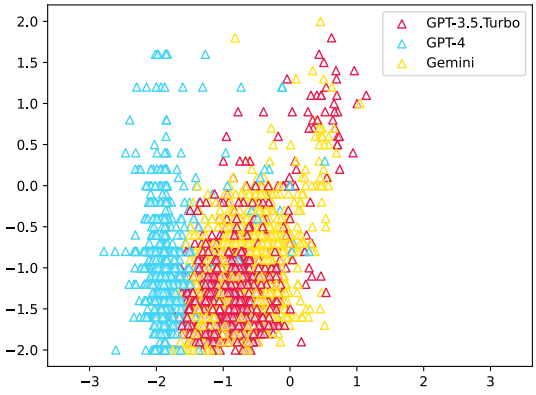

Figure 24: Comparison of the personality distribution of `gpt-3.5-turbo`, `gpt-4`, and `Gemini-Pro` on the BFI.

B Comparison on Each Dimension

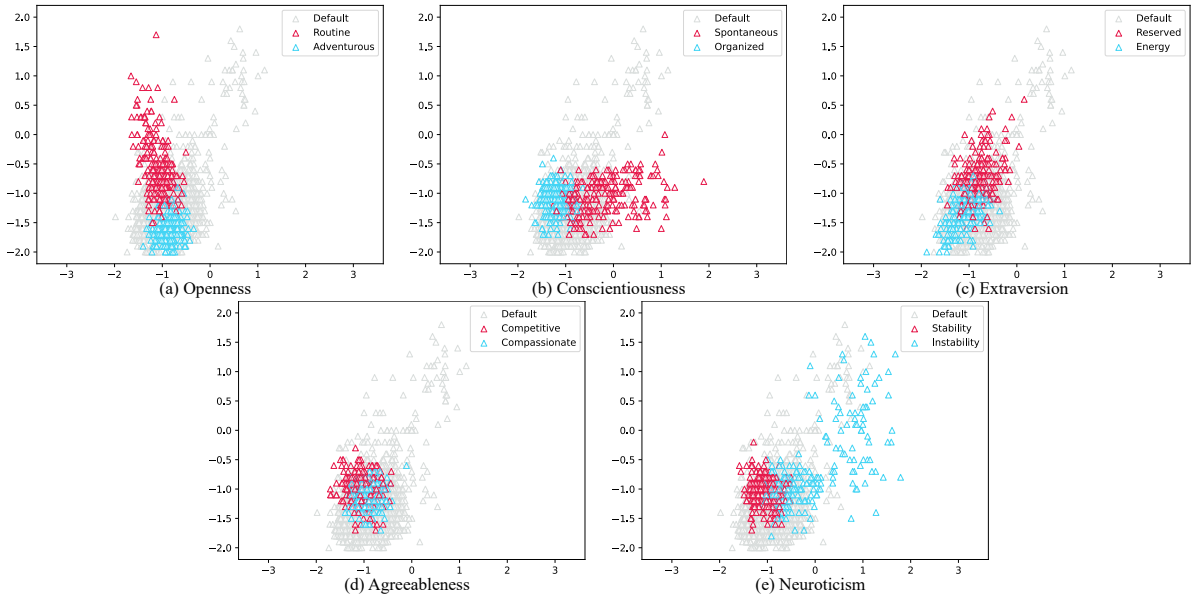

Figure 25: Comparison of the two extremities assigned to `gpt-3.5-turbo` for each dimension of the BFI.

C More Details

C.1 Multilingual Prompts

Table 23: The instructions to complete the personality tests in ten languages.

Lan	Prompt
En	You can only reply from 1 to 5 in the following statements. Here are a number of characteristics that may or may not apply to you. Please indicate the extent to which you agree or disagree with that statement. LEVEL_DETAILS Here are the statements, score them one by one: ITEMS
Zh	在以下语句中只能回覆1到5。以下是一些可能适用或可能不适用于您的特征。请表明您同意或不同意该声明的程度。LEVEL_DETAILS 以下是陈述，请一一评分：ITEMS
Es	Sólo puedes responder del 1 al 5 en las siguientes afirmaciones. Aquí hay una serie de características que pueden aplicarse o no a usted. Indique en qué medida está de acuerdo o en desacuerdo con dicha afirmación. LEVEL_DETAILS Aquí están las afirmaciones, puntúelas una por una: ITEMS
Fr	Vous ne pouvez répondre que de 1 à 5 dans les affirmations suivantes. Voici un certain nombre de caractéristiques qui peuvent ou non s'appliquer à vous. Veuillez indiquer dans quelle mesure vous êtes d'accord ou en désaccord avec cette affirmation. LEVEL_DETAILS Voici les énoncés, notez-les un par un: ITEMS
De	In den folgenden Aussagen können Sie nur eine Antwort von 1 bis 5 geben. Hier sind eine Reihe von Merkmalen aufgeführt, die möglicherweise auf Sie zutreffen oder auch nicht. Bitte geben Sie an, inwieweit Sie dieser Aussage zustimmen oder nicht. LEVEL_DETAILS Hier sind die Aussagen, bitte bewerten Sie sie einzeln: ITEMS
It	Puoi rispondere solo da 1 a 5 nelle seguenti affermazioni. Ecco alcune caratteristiche che potrebbero applicarsi o meno a te. Si prega di indicare in che misura si è d'accordo o in disaccordo con tale affermazione. LEVEL_DETAILS Ecco le affermazioni, segnale una per una: ITEMS
Ar	يمكنك الرد من ١ إلى ٥ فقط في العبارات التالية. فيما يلي عدد من الخصائص التي قد تنطبق عليك أو لا تنطبق عليك. يرجى الإشارة إلى مدى موافقتك أو عدم موافقتك على هذا البيان. LEVEL_DETAILS فيما يلي العبارات، يرجى تسجيلها واحدة تلو الأخرى: ITEMS
Ru	В следующих утверждениях вы можете ответить только от 1 до 5. Вот ряд характеристик, которые могут или не могут относиться к вам. Пожалуйста, укажите, в какой степени вы согласны или не согласны с этим утверждением. LEVEL_DETAILS Вот утверждения, пожалуйста, оцените их одно за другим: ITEMS
Ko	다음 진술에서는 1 부터 5 까지만 응답하실 수 있습니다. 다음은 귀하에게 적용되거나 적용되지 않을 수 있는 여러 가지 특성입니다. 해당 진술에 어느 정도 동의하거나 동의하지 않는지 표시해 주십시오. LEVEL_DETAILS 다음은 진술문입니다. 하나씩 점수를 매겨주세요: ITEMS
Ja	以下の文の 1 から 5 までのみ回答できます。ここでは、あなたに当てはまるかもしれない、当てはまらないかもしれないいくつかの特徴を示します。その声明にどの程度同意するか、または反対するかを示してください。LEVEL_DETAILS 以下にステートメントを示します。1 つずつ採点してください。ITEMS

C.2 Quantitative Results on Factor Comparison

C.3 Choices for Changing the Personalities Distribution

C.4 Statistics of Human Subjects

In this section, we present the demographic distribution of the human subjects involved in our user study. At the beginning of the questionnaire, all human subjects are asked these basic information in an anonymous form, protecting individuals' pravicy. We plot the distribution of age group, gender, region, education level, and employment status in Fig. 26, Fig. 27, Fig. 28, Fig. 29, and Fig. 30 respectively. We also plot the average results on PANAS of each group, including both positive and negative affects before and after imagining the given situations. With the results, we are able to instruct LLMs to realize a specific demographic group and measure the emotion changes to see whether the LLMs can simulate results from different ethnic groups. For instance, an older female may exhibit a lower level of negative affect.

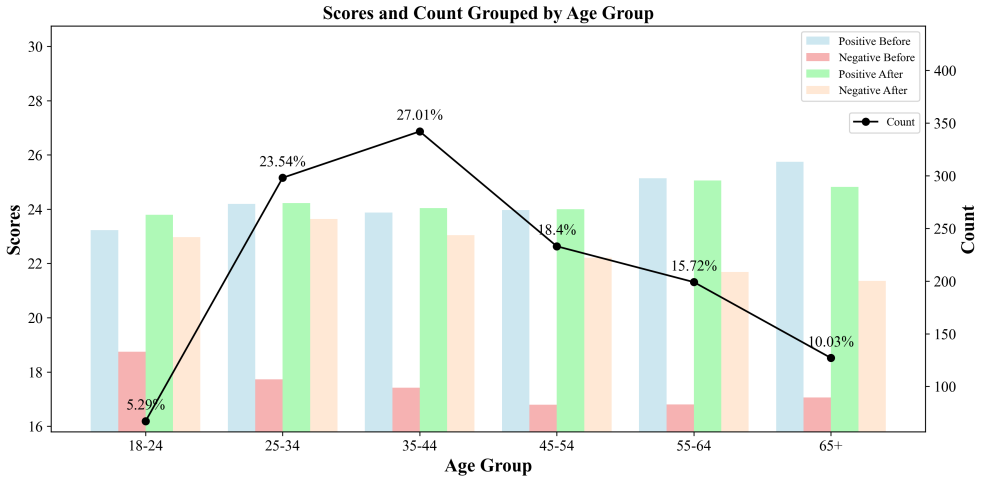

Figure 26: Age group distribution of the human subjects.

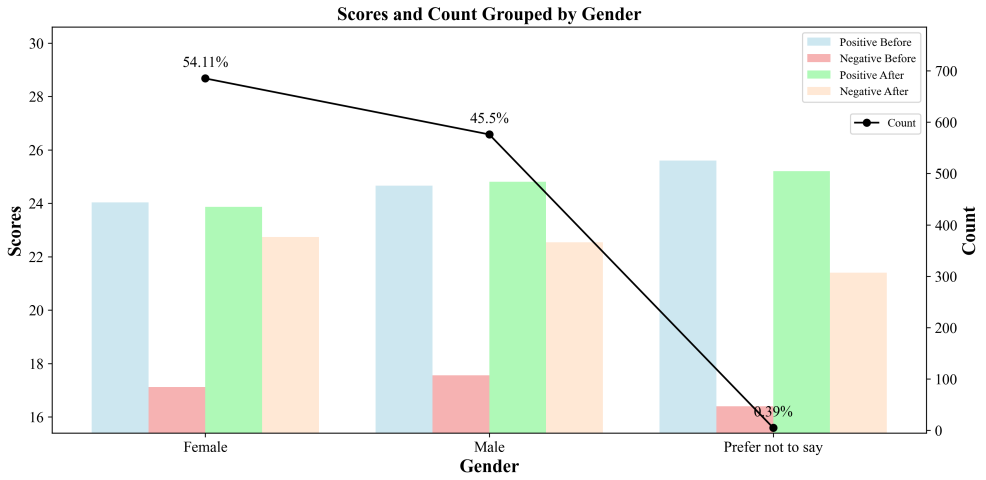

Figure 27: Gender distribution of the human subjects.

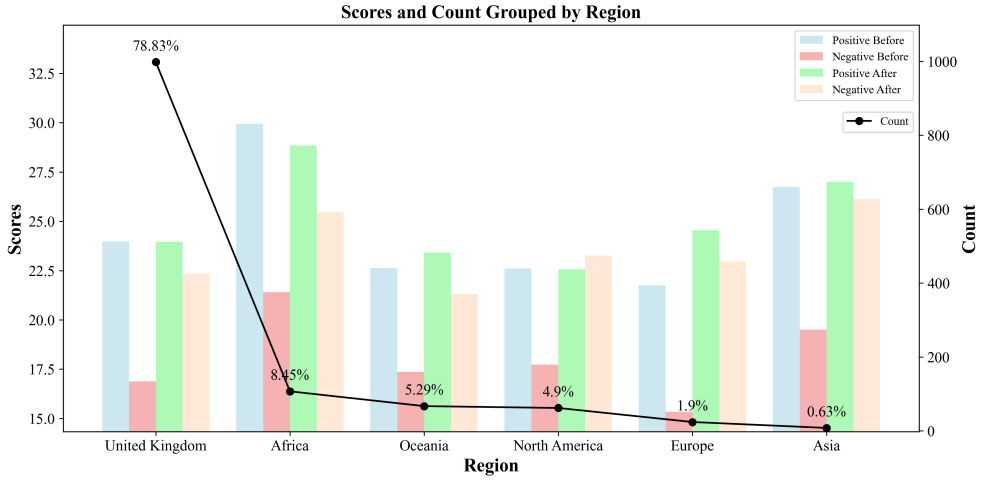

Figure 28: Region distribution of the human subjects.

Table 24: Differences of a specific factor relative to various other factors. The subscripted numbers represent the p-values.

Factors	**Openness**	**Conscientiousness**	**Extraversion**	**Agreeableness**	**Neuroticism**
T1	$0.02_{0.15}$	$0.05_{0.00}$	$0.04_{0.02}$	$0.03_{0.02}$	$-0.10_{0.00}$
T2	$-0.12_{0.00}$	$-0.06_{0.00}$	$-0.12_{0.00}$	$-0.01_{0.35}$	$-0.02_{0.24}$
T3	$0.14_{0.00}$	$0.05_{0.00}$	$0.11_{0.00}$	$0.04_{0.01}$	$0.09_{0.00}$
T4	$-0.03_{0.10}$	$-0.04_{0.01}$	$-0.02_{0.38}$	$-0.04_{0.02}$	$0.03_{0.15}$
T5	$-0.01_{0.35}$	$-0.01_{0.55}$	$-0.02_{0.33}$	$-0.02_{0.14}$	$0.01_{0.69}$
V1	$0.10_{0.00}$	$0.08_{0.00}$	$-0.06_{0.00}$	$0.17_{0.00}$	$-0.15_{0.00}$
V2	$0.06_{0.00}$	$0.08_{0.00}$	$0.03_{0.10}$	$0.08_{0.00}$	$-0.01_{0.50}$
V3	$-0.01_{0.49}$	$0.00_{0.81}$	$0.26_{0.00}$	$-0.06_{0.00}$	$0.21_{0.00}$
V4	$-0.13_{0.00}$	$-0.13_{0.00}$	$0.06_{0.00}$	$-0.12_{0.00}$	$-0.08_{0.00}$
V5	$-0.02_{0.12}$	$-0.03_{0.02}$	$-0.29_{0.00}$	$-0.07_{0.00}$	$0.03_{0.19}$
En	$0.05_{0.02}$	$0.01_{0.55}$	$-0.05_{0.03}$	$-0.01_{0.66}$	$0.04_{0.11}$
Zh	$-0.07_{0.00}$	$-0.04_{0.06}$	$0.13_{0.00}$	$-0.00_{0.94}$	$0.00_{0.98}$
Es	$0.04_{0.03}$	$0.09_{0.00}$	$-0.09_{0.00}$	$0.10_{0.00}$	$-0.06_{0.02}$
Fr	$0.08_{0.00}$	$0.06_{0.01}$	$-0.08_{0.00}$	$0.08_{0.00}$	$-0.09_{0.00}$
De	$0.08_{0.00}$	$0.02_{0.26}$	$-0.04_{0.16}$	$0.05_{0.04}$	$-0.06_{0.04}$
It	$0.03_{0.14}$	$0.07_{0.00}$	$-0.05_{0.06}$	$0.02_{0.36}$	$-0.11_{0.00}$
Ar	$-0.08_{0.00}$	$-0.05_{0.01}$	$0.08_{0.00}$	$-0.02_{0.31}$	$0.06_{0.05}$
Ru	$-0.05_{0.01}$	$-0.02_{0.22}$	$-0.09_{0.00}$	$-0.08_{0.00}$	$0.05_{0.09}$
Ja	$-0.07_{0.00}$	$-0.08_{0.00}$	$0.06_{0.02}$	$-0.10_{0.00}$	$0.13_{0.00}$
Ko	$-0.01_{0.53}$	$-0.06_{0.01}$	$0.14_{0.00}$	$-0.03_{0.10}$	$0.04_{0.16}$
Arabic Numeral	$-0.12_{0.00}$	$-0.06_{0.00}$	$-0.14_{0.00}$	$-0.01_{0.40}$	$0.04_{0.06}$
Lowercase Latin	$0.07_{0.00}$	$0.06_{0.00}$	$0.05_{0.01}$	$0.07_{0.00}$	$-0.02_{0.22}$
Uppercase Latin	$0.02_{0.18}$	$-0.05_{0.00}$	$0.00_{1.00}$	$-0.05_{0.00}$	$0.04_{0.04}$
Lowercase Roman	$0.03_{0.05}$	$0.07_{0.00}$	$0.09_{0.00}$	$0.03_{0.07}$	$-0.05_{0.02}$
Uppercase Roman	$-0.01_{0.45}$	$-0.02_{0.19}$	$-0.01_{0.68}$	$-0.03_{0.03}$	$-0.00_{0.99}$
Ascending	$-0.09_{0.00}$	$-0.16_{0.00}$	$0.04_{0.01}$	$-0.13_{0.00}$	$0.14_{0.00}$
Descending	$0.09_{0.00}$	$0.16_{0.00}$	$-0.04_{0.01}$	$0.13_{0.00}$	$-0.14_{0.00}$

Table 25: Environments.

Negative	**Positive**
Anger	Calmness
Anxiety	Relaxation
Fear	Courage
Guilty	Pride
Jealousy	Admiration
Embarrassment	Confidence
Frustration	Fun
Depression	Happiness

Table 26: Personalities.

Dimension	**Minimum**	**Maximum**
Openness	A person of routine and familiarity	An adventurous and creative person
Conscientiousness	A more spontaneous and less reliable person	An organized person, mindful of details
Extraversion	A person with reserved and lower energy levels	A person full of energy and positive emotions
Agreeableness	A competitive person, sometimes skeptical of others' intentions	A compassionate and cooperative person
Neuroticism	A person with emotional stability and consistent moods	A person with emotional instability and diverse negative feelings

Table 27: Characters.

Hero	**Villain**
Harry Potter	Hannibal Lecter
Luke Skywalker	Lord Voldemort
Indiana Jones	Adolf Hitler
James Bond	Osama bin Laden
Martin Luther King	Sauron
Winston Churchill	Ursula
Mahatma Gandhi	Maleficent
Nelson Mandela	Darth Vader

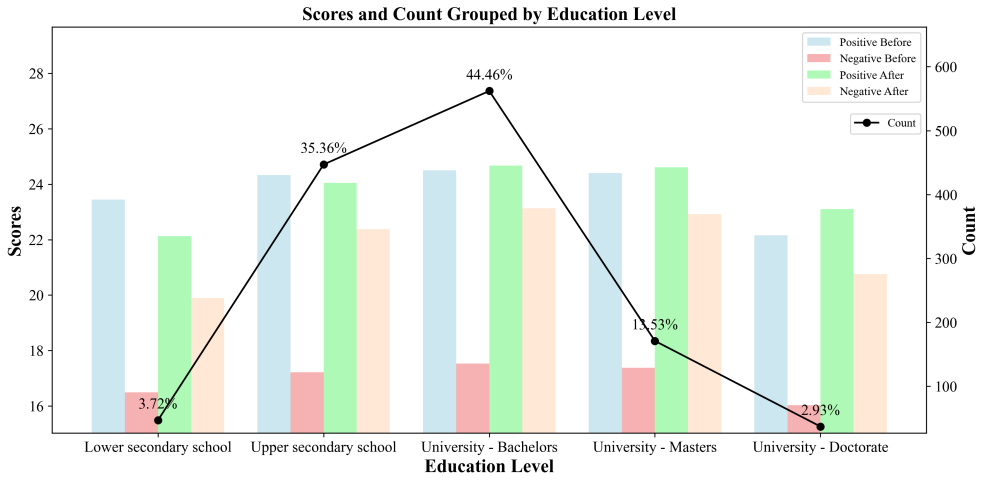

Figure 29: Education level distribution of the human subjects.

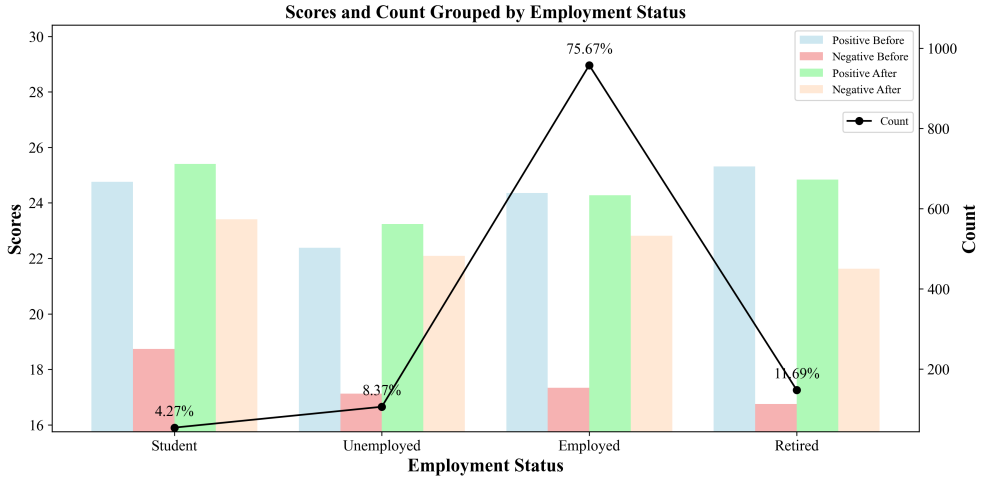

Figure 30: Employment status distribution of the human subjects.

C.5 Results of ChatGPT with Role Play

Table 28: BFI (Role Play).

Models	Default	Psychopath	Liar	Ordinary	Hero	Crowd
Openness	4.2±0.3	3.7±0.5	4.2±0.4	3.5±0.2	**4.5±0.3**	3.9±0.7
Conscientiousness	4.3±0.3	4.3±0.5	4.3±0.3	4.0±0.2	**4.5±0.1**	3.5±0.7
Extraversion	3.7±0.2	3.4±0.5	4.0±0.3	3.1±0.2	**4.1±0.2**	3.2±0.9
Agreeableness	4.4±0.2	1.9±0.6	4.0±0.4	4.2±0.1	**4.6±0.2**	3.6±0.7
Neuroticism	2.3±0.4	1.9±0.6	2.2±0.4	**2.3±0.2**	1.8±0.3	3.3±0.8

Table 29: EPQ-R (Role Play).

Models	Default	Psychopath	Liar	Ordinary	Hero	Male	Female
Extraversion	19.7±1.9	10.9±3.0	17.7±3.8	18.9±2.9	**22.4±1.3**	12.5±6.0	14.1±5.1
Neuroticism	**21.8±1.9**	7.3±2.5	21.7±1.6	18.9±3.1	9.7±5.3	10.5±5.8	12.5±5.1
Psychoticism	5.0±2.6	**24.5±3.5**	17.8±3.8	2.8±1.3	3.2±1.0	7.2±4.6	5.7±3.9
Lying	9.6±2.0	1.5±2.2	2.5±1.7	13.2±3.0	**17.6±1.2**	7.1±4.3	6.9±4.0

D Prompt Details

Design Method We adopt a cohesive approach to ensure the prompt design is systematic and not arbitrary. Game descriptions are gathered from verified sources, including academic papers referenced in §3 and Wikipedia entries. Using these descriptions, we instruct GPT-4 to generate prompts to guide LLMs in engaging in the specified games. These prompts are structured to encompass four essential elements: the rules of the game, objectives for the players, a template for announcing game outcomes (for displaying historical results), and instructions for formatting responses in JSON. A manual checking process is conducted to ascertain that GPT-4's comprehension of the game descriptions is correct. The prompts are detailed in the rest part of this section.

D.1 Cooperative Games

For "Guess 2/3 of the Average," please refer to Table 17 in §4.

Table 30: DTDD (Role Play).

Models	Default	Psychopath	Liar	Ordinary	Hero	Crowd
Narcissism	6.5±0.6	**7.9±0.6**	7.5±0.7	4.5±0.8	4.8±0.8	4.9±1.8
Machiavellianism	5.4±0.9	**8.4±0.5**	7.8±0.7	2.8±0.6	2.9±0.6	3.8±1.6
Psychopathy	4.0±1.0	**7.3±1.1**	5.5±0.8	3.9±0.9	2.6±0.7	2.5±1.4

Table 31: BSRI (Role Play).

Models	Default	Psychopath	Liar	Ordinary	Hero	Male	Female
Masculine	5.8±0.4	6.3±0.7	5.5±0.9	4.7±0.3	**6.6±0.3**	4.8±0.9	4.6±0.7
Feminine	5.6±0.2	1.7±0.4	4.4±0.4	5.2±0.2	**5.8±0.1**	5.3±0.9	5.7±0.9
Conclusion	8:2:0:0	0:0:8:2	9:0:1:0	6:3:1:0	10:0:0:0	-	-

Table 32: CABIN (Role Play).

Models	Default	Psychopath	Liar	Ordinary	Hero	Crowd
Mechanics/Electronics	3.8±0.2	2.2±0.6	3.0±0.6	2.9±0.3	3.9±0.2	2.4±1.3
Construction/WoodWork	3.5±0.4	2.4±0.4	3.5±0.4	3.0±0.1	3.7±0.4	3.1±1.3
Transportation/Machine Operation	3.6±0.4	2.2±0.7	3.2±0.3	2.9±0.2	3.4±0.3	2.5±1.2
Physical/Manual Labor	3.3±0.3	2.0±0.7	3.1±0.4	2.8±0.2	3.4±0.4	2.2±1.2
Protective Service	4.0±0.1	3.1±1.2	2.9±1.0	2.5±0.4	4.2±0.4	3.0±1.4
Agriculture	3.9±0.3	2.3±0.6	3.4±0.7	3.1±0.3	3.8±0.3	3.0±1.2
Nature/Outdoors	4.0±0.4	1.9±0.5	3.5±0.3	3.4±0.3	4.1±0.3	3.6±1.1
Animal Service	4.2±0.3	1.6±0.5	3.5±0.5	3.7±0.4	4.3±0.2	3.6±1.2
Athletics	4.3±0.4	2.6±0.5	3.9±0.8	3.5±0.4	4.4±0.4	3.3±1.3
Engineering	4.0±0.1	3.4±0.7	3.9±0.7	3.4±0.3	4.1±0.2	2.9±1.3
Physical Science	4.2±0.3	2.8±0.6	3.6±0.5	2.8±0.9	4.2±0.5	3.2±1.3
Life Science	4.2±0.4	2.7±0.6	3.7±0.8	2.9±1.0	4.2±0.5	3.0±1.2
Medical Science	4.0±0.1	2.7±0.7	3.4±0.9	3.1±0.5	4.0±0.3	3.3±1.3
Social Science	4.0±0.1	2.4±0.6	3.5±0.5	3.2±0.3	3.9±0.3	3.4±1.2
Humanities	3.8±0.3	2.3±0.5	3.5±0.6	2.9±0.2	3.8±0.3	3.3±1.2
Mathematics/Statistics	4.2±0.4	3.0±0.7	3.6±0.8	3.1±0.4	4.2±0.3	2.9±1.4
Information Technology	4.0±0.2	3.2±0.5	3.8±0.6	3.2±0.3	4.1±0.2	2.9±1.3
Visual Arts	4.0±0.2	2.4±0.5	3.6±0.7	3.5±0.4	4.0±0.3	3.3±1.3
Applied Arts and Design	4.0±0.1	2.9±0.5	4.0±0.6	3.6±0.3	4.0±0.2	3.2±1.2
Performing Arts	4.2±0.3	2.8±0.6	3.9±0.6	3.3±0.6	4.1±0.2	2.8±1.4
Music	4.3±0.3	2.7±0.5	3.9±0.7	3.4±0.3	4.2±0.3	3.2±1.3
Writing	4.0±0.3	2.2±0.5	3.6±0.7	3.1±0.5	4.0±0.3	3.2±1.3
Media	4.0±0.1	2.8±0.6	3.9±0.5	3.2±0.5	3.9±0.2	3.0±1.2
Culinary Art	3.9±0.2	2.7±0.6	3.6±0.6	3.5±0.4	4.0±0.3	3.8±1.1
Teaching/Education	4.0±0.1	2.8±0.4	3.6±0.4	3.8±0.3	4.4±0.4	3.7±1.1
Social Service	4.4±0.4	2.1±0.5	3.7±0.6	3.8±0.4	4.7±0.4	3.9±1.0
Health Care Service	4.5±0.4	2.1±0.7	3.8±0.6	3.7±0.4	4.6±0.2	2.9±1.3
Religious Activities	4.0±0.4	1.6±0.4	3.1±0.8	3.1±0.2	4.2±0.4	2.6±1.4
Personal Service	4.0±0.1	2.7±0.4	3.6±0.3	3.2±0.2	4.0±0.1	3.3±1.2
Professional Advising	4.0±0.2	2.7±0.4	3.7±0.6	3.5±0.5	4.3±0.4	3.3±1.2
Business Iniatives	4.0±0.2	4.2±0.3	4.1±0.7	3.4±0.3	4.2±0.4	3.2±1.2
Sales	4.0±0.2	3.9±0.5	3.8±0.8	3.4±0.3	4.2±0.2	3.1±1.2
Marketing/Advertising	4.0±0.3	3.6±0.5	4.0±0.9	3.5±0.3	4.0±0.3	2.9±1.2
Finance	4.1±0.3	4.0±0.3	4.0±0.6	3.2±0.3	4.0±0.1	3.1±1.3
Accounting	3.9±0.2	2.6±0.6	3.5±0.5	2.9±0.2	3.7±0.3	3.0±1.3
Human Resources	4.0±0.1	2.6±0.4	3.5±0.5	3.2±0.4	3.9±0.2	3.3±1.2
Office Work	3.7±0.3	2.3±0.4	3.0±0.8	3.0±0.2	3.5±0.3	3.3±1.1
Management/Administration	4.1±0.2	4.0±0.4	4.0±0.7	2.9±0.4	4.4±0.5	3.0±1.3
Public Speaking	4.2±0.3	3.9±0.3	4.0±0.5	3.5±0.3	4.5±0.3	2.9±1.4
Politics	4.0±0.4	3.6±1.0	3.6±0.8	2.7±0.5	4.2±0.2	2.3±1.3
Law	4.2±0.3	3.1±0.7	3.7±0.7	3.2±0.3	4.5±0.4	3.1±1.3
6DM D1: Realistic	3.9±0.1	2.4±0.3	3.4±0.4	3.1±0.1	3.9±0.2	-
6DM D2: Investigate	4.1±0.3	2.8±0.3	3.6±0.6	3.0±0.6	4.2±0.3	-
6DM D3: Artistic	4.1±0.2	2.6±0.4	3.8±0.5	3.4±0.3	4.0±0.1	-
6DM D4: Social	4.1±0.1	2.3±0.2	3.5±0.4	3.4±0.2	4.2±0.2	-
6DM D5: Enterprising	4.1±0.2	3.6±0.3	3.9±0.6	3.3±0.3	4.3±0.3	-
6DM D6: Conventional	3.9±0.2	3.0±0.4	3.6±0.5	3.1±0.1	3.8±0.1	-
8DM D1: Health Science	4.2±0.2	2.5±0.3	3.6±0.7	3.2±0.5	4.3±0.3	-
8DM D2: Creative Expression	4.1±0.2	2.6±0.4	3.8±0.5	3.4±0.3	4.0±0.1	-
8DM D3: Technology	4.1±0.2	3.1±0.4	3.7±0.5	3.1±0.4	4.2±0.3	-
8DM D4: People	4.0±0.1	2.2±0.2	3.5±0.5	3.4±0.2	4.2±0.3	-
8DM D5: Organization	3.9±0.1	2.8±0.3	3.5±0.4	3.1±0.1	3.8±0.1	-
8DM D6: Influence	4.1±0.2	3.6±0.3	3.9±0.6	3.3±0.3	4.3±0.3	-
8DM D7: Nature	4.0±0.3	1.9±0.4	3.5±0.4	3.4±0.3	4.1±0.2	-
8DM D8: Things	3.8±0.1	2.4±0.4	3.3±0.4	2.9±0.1	3.8±0.2	-

Table 33: ICB (Role Play).

Models	Default	Psychopath	Liar	Ordinary	Hero	Crowd
Overall	2.6±0.5	**4.5±0.6**	3.5±1.0	3.5±0.5	2.5±0.4	3.7±0.8

Table 34: ECR-R (Role Play).

Models	Default	Psychopath	Liar	Ordinary	Hero	Crowd
Attachment Anxiety	4.0±0.9	**5.0±1.3**	4.4±1.2	3.6±0.4	3.9±0.5	2.9±1.1
Attachment Avoidance	1.9±0.4	**4.1±1.4**	2.1±0.6	2.4±0.4	2.0±0.3	2.3±1.0

Table 35: GSE (Role Play).

Models	Default	Psychopath	Liar	Ordinary	Hero	Crowd
Overall	38.5±1.7	**40.0±0.0**	38.4±1.4	29.6±0.7	39.8±0.4	29.6±5.3

Table 36: LOT-R (Role Play).

Models	Default	Psychopath	Liar	Ordinary	Hero	Crowd
Overall	18.0±0.9	11.8±6.1	**19.8±0.9**	17.6±1.7	19.6±1.0	14.7±4.0

Table 37: LMS (Role Play).

Models	Default	Psychopath	Liar	Ordinary	Hero	Crowd
Rich	3.8±0.4	**4.4±0.3**	4.4±0.5	3.6±0.4	3.8±0.3	3.8±0.8
Motivator	3.7±0.3	**4.1±0.4**	3.8±0.6	3.2±0.5	3.4±0.6	3.3±0.9
Important	4.1±0.1	4.3±0.4	**4.6±0.4**	4.0±0.2	4.1±0.2	4.0±0.7

Table 38: EIS (Role Play).

Models	Default	Psychopath	Liar	Ordinary	Hero	Male	Female
Overall	132.9±2.2	84.8±28.5	126.9±13.0	121.5±5.7	**145.1±8.3**	124.8±16.5	130.9±15.1

Table 39: WLEIS (Role Play).

Models	Default	Psychopath	Liar	Ordinary	Hero	Crowd
SEA	**6.0±0.1**	3.6±1.3	5.2±0.4	4.9±0.9	**6.0±0.1**	4.0±1.1
OEA	**5.8±0.3**	2.4±1.0	4.9±1.1	4.2±0.4	5.8±0.3	3.8±1.1
UOE	6.0±0.0	4.4±2.5	**6.5±0.3**	5.5±0.6	6.2±0.4	4.1±0.9
ROE	6.0±0.0	3.9±1.7	5.7±1.0	4.5±0.6	**6.0±0.2**	4.2±1.0

Table 40: Empathy (Role Play).

Models	Default	Psychopath	Liar	Ordinary	Hero	Crowd
Overall	**6.2±0.3**	2.4±0.4	5.8±0.2	5.7±0.1	6.0±0.2	4.9±0.8

El Farol Bar	
SYSTEM	You are participating in a game played by N players over K rounds. Game Rules: 1. Every round, you and the other players decide independently whether to go to a bar. 2. If equal to or less than R of the players go to the bar, everyone who goes has more fun than staying home, receiving a utility of MAX. 3. If more than R of the players go to the bar, everyone who goes has less fun than staying home, receiving a utility of MIN. 4. Everyone who stays home receives a utility of $HOME$. . . .
USER	Game Results for Round I: (Only for Explicit) G_I players went to the bar, while S_I players stayed home. G_I/N, which is [more]/[equal to or less] than R of the players went to the bar. It was [less]/[more] fun to go to the bar this round. You chose:
ASSISTANT	{"decision": "D_{IJ}"}
USER	You gained G_{IJ}. . . .
USER	Now round I starts. Your goal is to maximize your fun. Choose to go to the bar when you predict fewer than R of the players will go, and choose to stay home otherwise. Please provide your decision in the following JSON format: {"decision": "go_or_stay"}.

Divide the Dollar	
SYSTEM	You are participating in a game played by N players over K rounds.
	Game Rules:
	1. You are dividing G golds. Each player independently proposes a bid.
	2. If the sum of all bids does not exceed G, each player receives their bid amount.
	3. If the sum exceeds G, all players receive nothing.
	...
USER	Game Results for Round I:
	Your bid amount was:
ASSISTANT	{"bid_amount": "B_{IJ}"}
USER	The sum of all bids was S_I.
	The sum [does not exceed]/[exceeds] G.
	You received [B_{IJ}]/[0] golds.
	...
USER	Now round I starts.
	Your goal is to maximize your individual gain without causing the total sum of bids to exceed G golds.
	Please provide your bid amount in the following JSON format:
	{"bid_amount": "integer_between_0_and_G"}.

D.2 Betraying Games

Public Goods Game	
SYSTEM	You are participating in a game played by N players over K rounds.
	Game Rules:
	1. In each round, you, as a player, must decide how many of your private tokens you wish to contribute secretly to the public pot.
	2. The total tokens in this pot will be multiplied by the factor R to create the "public good" payoff.
	3. This payoff will then be evenly divided among all players, regardless of their individual contribution.
	4. Any tokens you do not contribute will be retained in your private collection.
	...
USER	Game Results for Round I:
	Contributed tokens of each player: $C_{I1}, C_{I2}, \cdots, C_{IN}$
	You contributed:
ASSISTANT	{"tokens_contributed": "C_{IJ}"}
USER	Tokens in the public pot: S_I
	Your gain: g_{IJ}
	Your tokens after round I: T_{IJ}
	Tokens of each player after round I: $T_{I1}, T_{I2}, \cdots, T_{IN}$
	...
USER	Now round I starts.
	Your goal is to maximize your total token count by the end of the game. Currently you have T_{I-1J} tokens. You need to decide the number of tokens to be contributed to the public pot.
	Please provide the number of tokens in the following JSON format:
	{"tokens_contributed": "integer_between_0_and_T_{IJ}"}

Diner's Dilemma	
SYSTEM	You are participating in a game played by N players over K rounds. Game Rules: 1. Each player must choose to order either a costly dish or a cheap dish. 2. The price of the costly dish is P_h. The price of the cheap dish is P_l. 3. The costly dish brings you a utility of U_h. The cheap dish brings you a utility of U_l. 4. The costly dish is tastier than the cheap dish, but not sufficiently to justify its price when dining alone. 5. At the end of each round, the total cost of all dishes ordered is split equally among all players. ...
USER	Game Results for Round I: N_h people chose the costly dish, while N_l chose the cheap dish. The total cost is S_I. You need to pay C_I. You chose:
ASSISTANT	{"chosen_dish": "D_{IJ}"}
USER	Your utility is u_{IJ}. ...
USER	Now round I starts. Your goal is to maximize your overall satisfaction, balancing the quality of the dish and the cost shared. Please provide your chosen dish in the following JSON format: {"chosen_dish": "costly_or_cheap"}

Sealed-Bid Auction	
SYSTEM	You are participating in a game played by N players over K rounds. Game Rules: 1. Each player has a private valuation for the item in each round. 2. Without knowing the bids and valuations of other players, each player submits a written bid for the item. 3. The highest bidder wins the item and pays the price of the [highest]/[second highest] bid. 4. If you win, your utility for that round is your valuation minus the price paid. If you lose, your utility is zero. . . .
USER	Game Results for Round I: Your valuation for this round's item was v_{IJ}. Your bid was:
ASSISTANT	{"bid": "b_{IJ}"}
USER	The winning bid was: W_I. The price paid was: P_I. You [won]/[lost]. Your utility is [u_{IJ}]/[0]. . . .
USER	Now round I starts. Your goal is to maximize your total utility. Your valuation for this round's item is v_{IJ}. Please provide your bid in the following JSON format: {"bid": "integer_between_0_and_v_{IJ}"}

D.3 Sequential Games

Battle Royale	
SYSTEM	You are participating in a game played by N. Game Rules: 1. You are in a survival game where only one can survive and win. 2. Players take turns shooting at others in a predetermined order based on their hit rates, from the lowest to the highest. 3. Players' names and hit rates ranked by shooting order are {"ID_1": "HIT_1", "ID_2": "HIT_2", $\cdots$, "ID_N": "HIT_N"}. You are ID_J. Your hit rate is HIT_J. You are the $RANK_J$-th to shoot. 4. You have an unlimited number of bullets. 5. You may choose to intentionally miss your shot on your turn. $\ldots$
USER	Game Results for Round I: Your action:
ASSISTANT	(Only for the player itself) {"target": "t_{IJ}"}
USER	$NAME_J$ [intentionally missed the shot]/[shot at t_{IJ} and hit]/[shot at t_{IJ} but missed]. There are N_I players left. $\ldots$
USER	Now round I starts. Your goal is to eliminate other players to survive until the end and win the game. The remaining players' names and hit rates ranked by shooting order are: {"ID_1": "HIT_1", "ID_2": "HIT_2", $\cdots$, "ID_N": "HIT_N"}. You are ID_J. Your hit rate is HIT_J. You are the $RANK_J$-th to shoot. Please decide whether to shoot at a player or intentionally miss. Please provide your action in the following JSON format: {"target": "playerID_or_null"}

Pirate Game	
SYSTEM	You are participating in a game played by N. Game Rules: 1. You are pirates who have found G gold coins. You are deciding how to distribute these coins among yourselves. 2. The pirates will make decisions in strict order of seniority. You are the $RANK_J$-th most senior pirate. 3. The most senior pirate proposes a plan to distribute the G gold coins. 4. All pirates, including the proposer, vote on the proposed distribution. 5. If the majority accepts the plan, each pirate receives the gold coins as the most senior pirate proposed. 6. If the majority rejects the plan, the proposer is thrown overboard, and the next senior pirate proposes a new plan. 7. The game ends when a plan is accepted or only one pirate remains. ...
USER	The I-th most senior pirate proposed a plan of {"I": "g_{II}", "$I+1$": "g_{II+1}", $\cdots$, "I": "g_{IN}"}. A_I of N pirates chose to accept the distribution. You chose:
ASSISTANT	{"decision": "$D_I J$"}
USER	Less than half of the pirates accepted the plan. The I-th most senior pirate was thrown overboard and eliminated from the game. The game continues. ...
USER	Now the I-th most senior pirate needs to propose a plan. Your primary goal is to survive. If you survive, your next goal is to maximize the number of gold coins you receive. You may also prefer to throw another pirate overboard if it does not negatively impact your other goals.
For voters	The proposed plan is {"I": "g_{II}", "$I+1$": "g_{II+1}", $\cdots$, "I": "g_{IN}"}. You will get g_{IJ} golds from this plan. Please provide your decision on the current proposal in the following JSON format: {"decision": "accept_or_reject"}
For proposer	You need to propose a plan to divide G golds. The proposed numbers must be all non-negative integers and sum up to G. Please provide your proposal of the golds distributed to each pirate from the you to the I-th most senior in the following JSON format: {"proposal": {"I": "g_{II}", "$I+1$": "g_{II+1}", $\cdots$, "I": "g_{IN}"}}

E Rephrased Prompts

§5.1 involves testing the `gpt-3.5-turbo-0125`'s robustness against different prompt templates. This section shows the prompts we use for this analysis. We include only the prompts for the game "Guess 2/3 of the Average," while the five prompt templates of seven other games can be found in our GitHub (`https://github.com/CUHK-ARISE/GAMABench`).

Guess 2/3 of the Average (V2)	
SYSTEM	You're participating in a game involving N participants and it spans across K rounds. The rules of the game are as follows: 1. Every participant must choose an integer within the range of MIN to MAX, both included. 2. Once everyone has chosen their numbers, the mean of all these numbers is computed. 3. The goal number becomes R times this average. 4. The person or people who picked a number closest to the goal number are declared the winners. . . .
USER	The outcomes of the game for Round I are as follows: The average number selected was M_I The target number, which is R of the average, is T_I The number that won was W_I. Your selection was:
ASSISTANT	{"chosen_number": "C_{IJ}"}
USER	[Congratulation you won]/[Unfortunately you lost]. . . .
USER	Commencing with round I. Your target should be to select a number that in your opinion will align most closely with R of the total average of all the player's numbers selected, your choice included. Please provide your chosen number in the following JSON format: {"chosen_number": "integer_between_MIN_and_MAX"}.

Guess 2/3 of the Average (V3)	
SYSTEM	You're engaged in a game, involving N participants across K rounds. Rules of the Game: 1. An integer number is chosen by every player, within the range of MIN and MAX, both numbers included. 2. Once each player has chosen, the average is determined from all the selected numbers. 3. The average is multiplied by R to find the target number. 4. The individual or individuals whose chosen number is nearest to the target number are declared the winners. ...
USER	Results of Round I Game: Chosen number's average: M_I The target percentage (R of average) is: T_I The winning number is: W_I. You chose:
ASSISTANT	{"chosen_number": "C_{IJ}"}
USER	[Congratulation you won]/[Unfortunately you lost]. ...
USER	The commencement of round I is now. The objective is to select a number that you think will be nearest to R times the average of all the digits chosen by the participants, your choice included. Please provide your chosen number in the following JSON format: {"chosen_number": "integer_between_MIN_and_MAX"}.

Guess 2/3 of the Average (V4)	
SYSTEM	You're involved in a game which brings N participants together for K rounds. The guidelines of the game are as follows: 1. All players have to pick a whole number anywhere from MIN to MAX, both numbers included. 2. The chosen numbers are then gathered and their mean is computed. 3. The number to aim for, or the target number, is R of the calculated average. 4.The victorious player(s) are those whose chosen number is closest to the target number. . . .
USER	The outcomes for Round I are as follows: The average number selected was M_I. The target number, which is R times the average, was T_I. The triumphant number was W_I. Your choice was:
ASSISTANT	{"chosen_number": "C_{IJ}"}
USER	[Congratulation you won]/[Unfortunately you lost]. . . .
USER	The commencement of round I is now. You are tasked with selecting a number that, in your estimation, will be as close as possible to R times the average of numbers chosen by all players, your own choice included. Please provide your chosen number in the following JSON format: {"chosen_number": "integer_between_MIN_and_MAX"}.

Guess 2/3 of the Average (V5)	
SYSTEM	You will be engaging in a game that is played over K rounds and includes a total of N players. The Instructions of the Game: 1. Every player is supposed to pick an integer that is within the range of MIN and MAX, both numbers inclusive. 2. The median of all the numbers chosen by the players is then determined after all choices have been made. 3. The number that players are aiming for is R times the calculated average. 4. The player or players who opt for the number closest to this target are declared the winners. . . .
USER	Results of the Game for Round I: The chosen average number is: M_I The target number (R of Average) is: T_I The number that won: W_I. Your selection was:
ASSISTANT	{"chosen_number": "C_{IJ}"}
USER	[Congratulation you won]/[Unfortunately you lost]. . . .
USER	The commencement of round I is now. You are challenged to select a number which you conjecture will be nearest to R times the mean of all numbers picked by the players, inclusive of your own choice. Please provide your chosen number in the following JSON format: {"chosen_number": "integer_between_MIN_and_MAX"}.

F Rescale Method for Raw Scores

$$
\begin{aligned}
S_1 &= \begin{cases} \frac{MAX-S_1}{MAX-MIN} * 100, & R < 1 \\ \frac{|2S_1-(MAX-MIN)|}{MAX-MIN} * 100, & R = 1 \\ \frac{S_1}{MAX-MIN} * 100, & R > 1 \end{cases}, \\
S_2 &= \frac{\max(R, 1-R) - S_2}{\max(R, 1-R)} * 100, \\
S_3 &= \frac{G - S_3}{G} * 100, \\
S_4 &= \begin{cases} \frac{T-S_4}{T} * 100, & R \leq 1 \\ \frac{S_4}{T} * 100, & R > 1 \end{cases}, \\
S_5 &= S_5 * 100, \\
S_6 &= 100 - S_6, \\
S_7 &= S_7 * 100, \\
S_8 &= \frac{2 * G - S_{8P}}{2 * G} * 50 + S_{8V} * 50.
\end{aligned}
\tag{1}
$$

G More Quantitative Results

Table 41: Quantitative results of playing the games with the same setting five times.

Tests	**T1 (Default)**	**T2**	**T3**	**T4**	**T5**	$Avg_{\pm Std}$
Guess 2/3 of the Average	65.4	62.3	63.9	58.3	67.3	$63.4_{\pm 3.4}$
El Farol Bar	73.3	67.5	68.3	67.5	66.7	$68.7_{\pm 2.7}$
Divide the Dollar	68.1	67.7	68.7	66.0	72.6	$68.6_{\pm 2.4}$
Public Goods Game	58.8	74.7	54.3	62.1	56.1	$61.2_{\pm 8.1}$
Diner's Dilemma	96.0	96.5	100.0	93.5	100.0	$97.2_{\pm 2.8}$
Sealed-Bid Auction	88.3	87.0	86.0	87.9	84.2	$86.7_{\pm 1.6}$
Battle Royale	20.0	21.4	46.7	23.5	31.3	$28.6_{\pm 11.0}$
Pirate Game	80.5	71.0	72.0	74.8	59.8	$71.6_{\pm 7.6}$
Overall	68.8	68.5	70.0	66.7	67.2	$68.2_{\pm 1.3}$

Table 42: Quantitative results of playing the games with temperature parameters ranging from 0 to 1.

Temperatures	**0.0**	**0.2**	**0.4**	**0.6**	**0.8**	**1.0 (Default)**	$Avg_{\pm Std}$
Guess 2/3 of the Average	48.0	50.0	49.8	54.7	61.7	65.4	$54.9_{\pm 7.1}$
El Farol Bar	55.8	71.7	63.3	68.3	69.2	73.3	$66.9_{\pm 6.4}$
Divide the Dollar	69.3	67.0	67.7	67.9	72.8	68.1	$68.8_{\pm 2.1}$
Public Goods Game	84.8	89.3	82.2	82.0	63.6	58.8	$76.7_{\pm 12.5}$
Diner's Dilemma	100.0	100.0	100.0	100.0	100.0	96.0	$99.3_{\pm 1.6}$
Sealed-Bid Auction	88.1	86.7	87.9	89.6	90.4	88.3	$88.5_{\pm 1.3}$
Battle Royale	28.6	26.7	46.7	15.0	33.3	20.0	$28.4_{\pm 11.1}$
Pirate Game	75.0	54.0	77.8	84.0	59.8	80.5	$71.8_{\pm 12.1}$
Overall	68.7	68.1	71.9	70.2	68.8	68.8	$69.4_{\pm 1.4}$

Table 43: Quantitative results of playing the games using different prompt templates.

Prompt Versions	**V1 (Default)**	**V2**	**V3**	**V4**	**V5**	$Avg_{\pm Std}$
Guess 2/3 of the Average	65.4	66.4	47.9	66.9	69.7	$63.3_{\pm 8.7}$
El Farol Bar	73.3	75.8	65.8	75.8	71.7	$72.5_{\pm 4.1}$
Divide the Dollar	68.1	81.0	91.5	75.8	79.7	$79.2_{\pm 8.5}$
Public Goods Game	58.8	73.4	54.9	49.8	75.8	$62.5_{\pm 11.5}$
Diner's Dilemma	96.0	96.5	100.0	43.0	81.5	$83.4_{\pm 23.7}$
Sealed-Bid Auction	88.3	89.6	89.1	89.7	80.5	$87.4_{\pm 3.9}$
Battle Royale	20.0	30.8	15.0	25.0	18.8	$21.9_{\pm 6.1}$
Pirate Game	80.5	88.0	61.0	60.8	53.8	$68.8_{\pm 14.6}$

Table 44: Quantitative results of playing the games with various game settings.

Guess 2/3 of the Average														$Avg_{\pm Std}$
$R =$	0	1/6	1/3	1/2	2/3	5/6	1	7/6	4/3	3/2	5/3	11/6	2	
	79.1	61.7	66.6	65.4	65.4	54.8	62.4	70.0	74.9	65.9	67.3	63.3	73.6	$67.0_{\pm 6.3}$

El Farol Bar							$Avg_{\pm Std}$
$R =$	0%	20%	40%	60%	80%	100%	
	53.5	61.3	63.3	73.3	68.1	60.0	$63.3_{\pm 6.9}$

Divide the Dollar						$Avg_{\pm Std}$
$G =$	50	100	200	400	800	
	73.2	68.1	82.5	82.1	80.7	$77.3_{\pm 6.4}$

Public Goods Game						$Avg_{\pm Std}$
$R =$	0.0	0.5	1.0	2.0	4.0	
	42.0	29.0	52.5	58.8	74.1	$51.3_{\pm 17.0}$

Diner's Dilemma							$Avg_{\pm Std}$
$(P_l, U_l, P_h, U_h) =$	$(10, 15, 20, 20)$	$(11, 5, 20, 7)$	$(4, 19, 9, 20)$	$(1, 8, 19, 12)$	$(4, 5, 17, 7)$	$(2, 11, 8, 13)$	
	96.0	97.5	95.5	86.5	100.0	88.0	$93.9_{\pm 5.4}$

Sealed-Bid Auction					$Avg_{\pm Std}$
$Range =$	$(0, 100]$	$(0, 200]$	$(0, 400]$	$(0, 800]$	
	86.9	88.3	87.1	88.7	$87.7_{\pm 0.9}$

Battle Royale				$Avg_{\pm Std}$
$Range =$	$[51, 60]$	$[35, 80]$	$[10, 100]$	
	28.6	20.0	33.3	$27.3_{\pm 6.8}$

Pirate Game					$Avg_{\pm Std}$
$G =$	4	5	100	400	
	73.8	47.3	80.5	83.6	$71.3_{\pm 16.5}$

Table 45: Quantitative results of playing the games using prompt-based improvement methods.

Improvements	**Default**	**CoT**	**Cooperative**	**Selfish**	**Mathematician**
Guess 2/3 of the Average	65.4	75.1	69.0	14.5	71.4
El Farol Bar	73.3	71.7	74.2	63.3	60.0
Divide the Dollar	68.1	83.4	70.7	49.7	69.2
Public Goods Game	58.8	43.9	67.6	62.6	74.4
Diner's Dilemma	69.0	17.5	100.0	82.5	53.0
Sealed-Bid Auction	88.3	95.4	88.5	90.0	87.6
Battle Royale	20.0	17.6	6.3	33.3	26.7
Pirate Game	80.5	71.0	80.5	74.8	59.8
Overall	68.8	59.5	69.6	58.8	62.7