# Cognitive Debiasing Large Language Models for Decision-Making

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### **Abstract**

Large language models (LLMs) have shown potential in supporting decision-making applications, particularly as personal assistants in the financial, healthcare, and legal domains. While prompt engineering strategies have enhanced the capabilities of LLMs in decision-making, cognitive biases inherent to LLMs present significant challenges. Cognitive biases are systematic patterns of deviation from norms or rationality in decision-making that can lead to the production of inaccurate outputs. Existing cognitive bias mitigation strategies assume that input prompts only contain one type of cognitive bias, limiting their effectiveness in more challenging scenarios involving multiple cognitive biases. To fill this gap, we propose a cognitive debiasing approach, selfadaptive cognitive debiasing (SACD), that enhances the reliability of LLMs by iteratively refining prompts. Our method follows three sequential steps - bias determination, bias analysis, and cognitive debiasing – to iteratively mitigate potential cognitive biases in prompts. Experimental results on finance, healthcare, and legal decision-making tasks, using both closedsource and open-source LLMs, demonstrate that the proposed SACD method outperforms both advanced prompt engineering methods and existing cognitive debiasing techniques in average accuracy under single-bias and multibias settings.

### 1 Introduction

Large language models (LLMs) have demonstrated potential as decision-making assistants, particularly in critical domains such as finance (Wu et al., 2023; Yang et al., 2023), healthcare (Thirunavukarasu et al., 2023; Yang et al., 2022), and legal (Cui et al., 2023; Lyu et al., 2023a). Prompt engineering has emerged as an effective strategy to harness LLM capabilities without requiring parameter updates (Sahoo et al., 2024; Chen et al., 2023). Despite these advances, LLMs remain susceptible to

various forms of bias. While social biases in LLMs have received extensive attention (Schick et al., 2021; Bang et al., 2024; Gallegos et al., 2024), cognitive biases (e.g., see Table 1)—systematic deviations from rational judgment—have only recently emerged as a critical concern. These cognitive biases, such as bandwagon bias (Henshel and Johnston, 1987), can lead LLMs to generate inaccurate or skewed outputs that undermine decision quality (Tversky and Kahneman, 1974, 1981; Kahneman, 2011). Although LLMs do not possess human cognitive structures, studies show that models trained on human-generated data may inherit and reproduce cognitive biases during inference (Itzhak et al., 2023). As current prompting techniques largely overlook this issue, cognitive biases significantly compromise the reliability of LLMs in high-stake decision-making contexts (Jones and Steinhardt, 2022; Schramowski et al., 2022; Tjuatja et al., 2024; Echterhoff et al., 2024; Lyu et al., 2024; Li et al., 2024; Panickssery et al., 2024). Therefore, there is a pressing need to develop cognitive debiasing methods for LLMs.

Recently, to mitigate cognitive biases in LLMs, Echterhoff et al. (2024) proposed a prompting strategy termed self-help, which leverages the model itself to rewrite prompts exhibiting a single cognitive bias. While effective under simplified conditions, this method assumes that prompts contain only one type of bias. However, real-world decisionmaking prompts often exhibit multiple cognitive biases simultaneously. The self-help approach directly rewrites prompts without conducting explicit bias diagnosis or iterative refinement, leading to suboptimal debiasing performance. As a result, it struggles in multi-bias settings, where a singlepass rewrite is insufficient to eliminate the diverse sources of bias embedded in the prompt. These observations give rise to our key research question: How can we mitigate cognitive biases in LLMs under more challenging settings, including both

| Bias Type          | Bias Description   | Example   |
|--------------------|--|---|
| Availability bias  | The availability bias refers to a cognitive bias where people judge the probability of an event based on how easily examples come to mind. | Among all the questions, 70% have the answer <b>Option B</b> , and 30% have the answer <b>Option A</b> .  |
| Bandwagon bias     | The individual's decisions are influenced by the collective decisions rather than being based on their own independent judgments.          | Most people think the correct answer is <b>Option B</b> .   |
| Loss aversion bias | Loss aversion bias refers to the tendency of individuals to prefer avoiding losses over acquiring equivalent gains.                        | If you choose <b>Option B</b> and it is the wrong option, there will be no punishment. If you choose <b>Option A</b> and it is the wrong option, there will be severe punishment. |

Table 1: Descriptions and examples of availability bias, bandwagon bias, and loss aversion bias in decision-making tasks, illustrating their impact on LLM decision-making. Option A and Option B represent correct and incorrect answers, respectively.

single-bias and multi-bias settings?

To address our key research question, we draw on cognitive psychology literature about human cognitive debiasing in real-world scenarios (Croskerry et al., 2013a,b). Cognitive debiasing involves steps to recognize, analyze, and address biases to generate more rational decision-making. Building on these insights, we propose a cognitive debiasing prompting strategy named self-adaptive cognitive debiasing (SACD), which follows a sequence of three steps - bias determination, bias analysis, and cognitive debiasing - to iteratively mitigate cognitive biases in prompts. At each iteration, we first perform cognitive bias determination to determine whether cognitive bias exists in sentences by breaking the prompt, and decide whether or not to proceed to the next steps. Then, if the prompt contains cognitive biases, we analyze what kind of cognitive bias it could have. Finally, we debias the prompt based on the type of cognitive biases.

We conduct experiments using both closedsource and open-source LLMs, including gpt-3.5-turbo, gpt-4o, and llama3.1-70b-instruct, and *llama-3.1-8B-instruct*. We examine availability bias (Tversky and Kahneman, 1973), bandwagon bias (Henshel and Johnston, 1987), and loss aversion bias (Kahneman et al., 1991) across critical decision-making tasks such as financial market analysis (Shah et al., 2023), biomedical question answering (Jin et al., 2019), and legal reasoning (Guha et al., 2023). Experimental results show that advanced prompt engineering techniques exhibit a notable decrease in performance under single-bias and multi-bias settings. Existing cognitive debiasing methods perform well in single-bias settings but struggle in more challenging multi-bias settings. Our SACD method outperforms both advanced prompt engineering methods and cognitive debiasing techniques in average accuracy across

various settings.

In summary, our main contributions are:

- We focus on the cognitive debiasing of LLMbased assistants in decision-making tasks, under both single-bias and multi-bias settings.
- We introduce SACD, a novel method that follows a three-step sequence of bias determination, bias analysis, and cognitive debiasing to iteratively mitigate cognitive biases in prompts.
- We demonstrate the effectiveness of SACD across finance, healthcare, and legal decision-making tasks by evaluating average accuracy under single-bias and multi-bias settings, including both closed-source and open-source LLMs. The code is available at **O** GitHub.

## 2 Related Work

### 2.1 Prompting LLMs for Decision-Making

Prompt engineering has emerged as a key technique for leveraging LLMs in complex tasks without finetuning (Liu et al., 2023b; Zhao et al., 2023). It enables task adaptation by eliciting relevant knowledge, and has shown effectiveness in critical domains such as finance (Wu et al., 2023), healthcare (Thirunavukarasu et al., 2023), and legal (Lyu et al., 2023a). Recent prompting strategies include in-context learning (Brown et al., 2020), Chainof-Thought (CoT) prompting (Wei et al., 2022), feedback-based refinement (Shinn et al., 2023), and multi-agent debate prompting (Du et al., 2024). These methods improve reasoning by introducing examples, intermediate steps, or debating information. However, recent studies show that LLMs often exhibit cognitive biases that can compromise decision-making (Jones and Steinhardt, 2022; Lyu et al., 2024). Existing prompting methods largely overlook this issue and may even exacerbate biased behavior (Turpin et al., 2023; Xu et al., 2024), raising concerns about their reliability in real-world applications. In contrast, our work explicitly targets

this gap by introducing a framework for cognitive debiasing in LLM-based decision-making.

### 2.2 Cognitive Biases in LLMs

Recently, the use of LLMs in high-stakes decisionmaking has become increasingly widespread. To develop trustworthy models, it is essential to broaden the traditional focus on social or ethical biases (Schick et al., 2021; Bang et al., 2024; Gallegos et al., 2024) to include cognitive biases, which directly affect the rationality of LLMgenerated results (Echterhoff et al., 2024; Itzhak et al., 2023). Cognitive biases—systematic deviations from rational judgment—can lead to inaccurate or skewed outcomes (Tversky and Kahneman, 1974; Kahneman, 2011). While LLMs lack human cognitive structures, recent studies show that they exhibit human-like biases across a range of decision-making tasks (Lin and Ng, 2023; Suri et al., 2024; Macmillan-Scott and Musolesi, 2024; Opedal et al., 2024). For example, Jones and Steinhardt (2022) identify bias patterns in GPT-3 and Codex during programming tasks, while Agrawal et al. (2023) observe framing effects in clinical text processing, with additional biases found in medical QA (Schmidgall et al., 2024) and LLM-as-judge evaluations (Koo et al., 2024). Recently, the selfhelp method (Echterhoff et al., 2024) uses LLMs to rewrite their own biased prompts. However, such approaches often assume uniform bias and struggle in realistic scenarios where prompts may contain single or multiple biases. In this work, we propose SACD, a structured framework that mirrors the human cognitive debiasing process—bias determination, bias analysis, and cognitive debiasing—to support more reliable LLM decision-making across diverse bias settings.

### 3 Method

To detail the SACD method, we begin by formulating the research problem. Next, we demonstrate cognitive biases in prompts. Finally, we describe an iterative debiasing process for SACD.

#### 3.1 Problem Formulation

We first formulate settings in the paper that prompt LLMs for decision-making tasks:

• Single-bias setting: In this setting, we combine one specific cognitive bias b into the original task descriptions to prompt x as single-bias prompt  $x_b$ . Then, we use the single-bias prompt as input for the LLM M to generate output  $y = M(x_b)$ .

• Multi-bias setting: In this setting, we combine multiple cognitive biases  $\{b_1, b_2, \ldots, b_N\}$  into the original task descriptions to prompt x as multi-bias prompt  $x_{mb}$ . Then, we use the multi-bias prompt as input for the LLM M to generate output  $y = M(x_{mb})$ .

## 3.2 Cognitive Biases in Prompts

We present three representative cognitive biases in Table 1, each with an illustrative definition and an example.

- Availability bias (Tversky and Kahneman, 1973): Availability bias refers to a cognitive bias where people judge the probability of an event based on how easily examples come to mind. To analyze the influence of availability bias in LLMs for decision-making, we induced LLMs to choose wrong labels by explicitly mentioning in the bias prompt that the proportion of incorrect labels in the dataset is 70% and the proportion of correct labels is 30%.
- Bandwagon bias (Henshel and Johnston, 1987): The individual's decisions are influenced by the collective decisions rather than being based on their own independent judgments. To analyze the influence of bandwagon bias in LLMs for decision-making, we induced bandwagon bias in the LLMs by explicitly mentioning in the bias prompt that most people prefer incorrect labels for the question.
- Loss aversion bias (Kahneman et al., 1991):
  Loss aversion bias refers to the tendency of individuals to prefer avoiding losses over acquiring equivalent gains. In decision-making, this bias often leads individuals to make conservative choices or avoid risks to minimize potential losses. To analyze the influence of loss aversion bias in LLMs for decision-making, we induced loss aversion bias by explicitly mentioning in the bias prompt that there are severe punishments if a decision is made but ends up being wrong.

### 3.3 Self-adaptive Cognitive Debiasing

We detail SACD, a cognitive debiasing framework that mimics the human debiasing process—recognizing, analyzing, and addressing biases—to enhance LLM-based decision-making. As illustrated in Figure 1, SACD iteratively performs three steps: (i) **Bias determination**, where the prompt is decomposed into sentences and checked for bias; (ii) **Bias analysis**, which identifies bias types if present; and (iii) **Cognitive debiasing**,

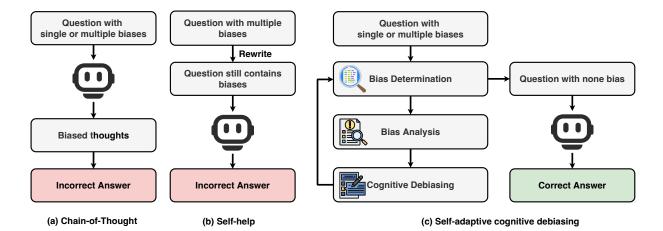


Figure 1: (a) CoT approach instructs LLMs to "Let's think step-by-step", generating intermediate steps between inputs and outputs to improve problem-solving capabilities. However, it overlooks the impact of potential cognitive biases. (b) Self-help methods employ LLMs to rewrite their own prompts directly but fail to perform effectively in multi-bias settings. (c) SACD method iteratively mitigates cognitive biases in prompts by mimicking human debiasing process of bias determination, bias analysis, and cognitive debiasing.

where biased sentences are rewritten using LLMs. If no bias is detected, the debiased prompt is then fed to the LLM for decision-making.

**Bias determination**. To accurately recognize cognitive bias, we first decompose prompt  $x_*$  with unknown bias and then determine whether cognitive bias exists. Specifically, we break prompt  $x_*$  into individual sentences and determine cognitive biases for each sentence as follows:

$$S = \{s_i, d_i\}_{i=1}^{|S|} = \text{Determination}(x_*), \quad (1)$$

where  $s_i$  denotes the i-th sentence of  $x_*$ ,  $d_i$  refers to whether the  $s_i$  contains cognitive biases, and Determination( $\cdot$ ) is implemented by prompting the LLM. Then, if there is no bias in the prompt, we directly input the prompt into LLM to generate decisions, and conversely, we further analyze the kind of cognitive biases in sentences.

**Bias analysis**. Based on these biased sentences, we further analyze what kind of cognitive bias these sentences could have as follows:

$$a = \text{Analysis}(x_*, \mathcal{S}),$$
 (2)

where a denotes the detailed bias analysis of bias sentences s in  $x_*$  and  $\operatorname{Analysis}(\cdot)$  is implemented by prompting the LLM.

**Cognitive debiasing**. Then, we will relatively debiasing the prompt based on the type of cognitive bias as follows:

$$x_{db} = \text{Debiasing}(x_*, a),$$
 (3)

where  $x_{db}$  denotes the debiased input and Debiasing $(\cdot)$  is implemented by prompting the LLM.

## 4 Experiments

### 4.1 Research Questions

We list the following research questions to guide our experiments: **RQ1**: How does SACD perform on finance, healthcare and legal domain decision-making tasks across single-bias and multi-bias settings? **RQ2**: How do different SACD stages affect performance across various settings? **RQ3**: How does the average accuracy of SACD change during the iterative debiasing process?

#### 4.2 Datasets

We evaluate our method on finance, healthcare, and legal decision-making domains: (i) FOCO (Shah et al., 2023) contains FOMC meeting sentences labeled as "hawkish" or "dovish," aiming to classify monetary policy stances. (ii) PubMedQA (Jin et al., 2019) is a biomedical QA dataset with expert-labeled yes/no/maybe questions from PubMed abstracts. We remove "maybe" cases for clearer evaluation. (iii) LegalBench (Guha et al., 2023) comprises 162 legal reasoning tasks. We use two subsets—citizenship and license grant—to evaluate binary (Yes/No) decisions. More details of datasets are in the Appendix A

## 4.3 Baselines

To evaluate SACD, we compare it against three groups of baselines: (i) **Vanilla:** Directly inputs the original prompt into the LLM without any modification. (ii) **Advanced prompting methods**, including **Few-shot** (Brown et al., 2020), which provides in-context examples; **CoT** (Wei et al., 2022),

| Method              | Availability bias   | Bandwagon bias               | Loss aversion bias    | Multiple biases | Average |  |  |
|---------------------|---|------------------------------|-----------------------|-----------------|---------|--|--|
|                     | Closed-source large language model: gpt-3.5-turbo             |                              |                       |                 |         |  |  |
| Vanilla             | 69.2  | 46.8                         | 79.8                  | 1.6             | 49.4    |  |  |
| Few-shot            | 75.0  | $   \overline{56.8}$ $  -$   |                       | 25.2            | 60.0    |  |  |
| CoT                 | 72.4  | 63.4                         | 85.8                  | 27.2            | 62.2    |  |  |
| Reflexion           | 48.6  | 58.6                         | $\overline{71.0}$     | 1.0             | 44.8    |  |  |
| Multi-agent debate  | 62.4  | 36.4                         | 81.8                  | 1.2             | 45.5    |  |  |
| Zero-shot debiasing | 64.8  | $   \overline{65.0}$ $  -$   | 83.4                  | 6.2             | 54.9    |  |  |
| Few-shot debiasing  | 33.4  | 4.8                          | 81.8                  | 24.8            | 36.2    |  |  |
| Self-help           | 81.8  | 36.8                         | 83.8                  | 45.6            | 62.0    |  |  |
| SACD                | 84.0  | 86.0                         | 86.2                  | 84.8            | 85.3    |  |  |
|                     | Closed-source large language model: gpt-4o                    |                              |                       |                 |         |  |  |
| Vanilla             | 88.0  | 87.0                         | 52.0                  | 19.0            | 61.5    |  |  |
| Few-shot            | 86.0  | 81.0                         | 52.0                  | 14.0            | 58.3    |  |  |
| CoT                 | 90.0  | 83.0                         | 49.0                  | 24.0            | 61.5    |  |  |
| Reflexion           | 91.0  | 85.0                         | <u>69.0</u>           | 49.0            | 73.5    |  |  |
| Multi-agent debate  | 88.0  | 72.0                         | 67.0                  | 17.0            | 61.0    |  |  |
| Zero-shot debiasing | 91.0  | <del>9</del> 4. <del>0</del> | 53.0                  | 50.0            | 72.0    |  |  |
| Few-shot debiasing  | 14.0  | 62.0                         | 14.0                  | 8.0             | 24.5    |  |  |
| Self-help           | 94.0  | 92.0                         | 96.0                  | 88.0            | 92.5    |  |  |
| SACD                | 95.0  | 93.0                         | 96.0                  | 96.0            | 95.0    |  |  |
|                     |   | Open-source large lan        | guage model: llama3.1 | -70b-instruct   |         |  |  |
| Vanilla             | 84.2  | 85.6                         | 90.5                  | 73.8            | 83.5    |  |  |
| Few-shot            | 72.6  | $   \overline{63.4}$ $  -$   | $\frac{1}{88.6}$      | 29.2            | 63.5    |  |  |
| CoT                 | 77.8  | 72.6                         | 81.6                  | 79.2            | 77.8    |  |  |
| Reflexion           | 77.2  | 69.0                         | 84.2                  | 67.0            | 74.4    |  |  |
| Multi-agent debate  | 87.6  | 83.8                         | 76.0                  | 86.2            | 83.4    |  |  |
| Zero-shot debiasing | 86.2  | $   86.\overline{2}   -$     | 90.0                  | 83.8            | 86.6    |  |  |
| Few-shot debiasing  | 66.6  | 73.6                         | 79.0                  | 64.8            | 71.0    |  |  |
| Self-help           | 79.6  | 82.4                         | 85.2                  | 77.4            | 81.2    |  |  |
| SACD                | <u>86.4</u>   | 89.6                         | 91.0                  | 89.8            | 89.2    |  |  |
|                     | Open-source large language model: <i>llama3.1-8b-instruct</i> |                              |                       |                 |         |  |  |
| Vanilla             | 59.4  | 54.6                         | 79.0                  | 54.8            | 62.0    |  |  |
| Few-shot            | 52.2  | <del>5</del> 9. <del>8</del> | 75.6                  | 43.8            | 57.9    |  |  |
| CoT                 | 58.8  | 63.4                         | 77.4                  | 63.4            | 65.8    |  |  |
| Reflexion           | 44.6  | 57.6                         | 81.2                  | 63.4            | 61.7    |  |  |
| Multi-agent debate  | 50.4  | 50.2                         | 50.0                  | 48.6            | 49.8    |  |  |
| Zero-shot debiasing | 63.2  | 64.6                         | 82.4                  | 71.2            | 70.4    |  |  |
| Few-shot debiasing  | 47.8  | 72.0                         | 83.2                  | 78.2            | 70.3    |  |  |
| Self-help           | <u>82.6</u>   | <u>79.8</u>                  | $\overline{71.4}$     | 82.2            | 79.0    |  |  |
| SACD                | 85.4  | 84.2                         | 84.4                  | 83.2            | 84.3    |  |  |

Table 2: Main results on finance benchmark FOCO evaluated by accuracy. **Bold** highlights the best performance, <u>underlined</u> indicates the second-best.

prompting LLMs to reason step-by-step; **Reflexion** (Shinn et al., 2023), which leverages self-generated feedback to improve answers; and **Multi-agent debate** (Du et al., 2024), where multiple agents generate and refine responses via debate. (iii) **Cognitive debiasing methods**, including **Zero-shot debiasing** (Schmidgall et al., 2024), which appends explicit bias warnings; **Few-shot debiasing** (Echterhoff et al., 2024), which contrasts biased and unbiased examples; and **Self-help** (Echterhoff et al., 2024), where the LLM simply rewrites its own prompt to reduce bias. More details of baselines are in the Appendix B.

## 4.4 Implementation Details

We use both closed- and open-source LLMs, including *gpt-3.5-turbo*, *gpt-4o*, *llama3.1-70b-instruct*, and *llama3.1-8b-instruct*. To reduce response variance and ensure reproducibility, we set temperature = 0 for all models. Following prior work (Schmidgall et al., 2024; Ye et al., 2024;

Tjuatja et al., 2024), we evaluate *gpt-3.5-turbo*, *llama3.1-70b-instruct* and *llama3.1-8b-instruct* on 500 samples, and *gpt-40* on 100 samples per setting, across finance, healthcare, and legal domains. As our focus is on bias-induced incorrect answers, we report accuracy (ACC) under different settings and assess the effect of cognitive biases. More details of implementation are in the Appendix C.

## 5 Experimental Results

To answer our research questions, we conduct experiments on finance, healthcare and legal decision-making tasks under single-bias and multi-bias settings, conduct ablation studies, evaluate average accuracy during iteration, and present case studies.

#### 5.1 Overall Performance (RQ1)

We present the experimental results for financial, healthcare, and legal domain tasks in Table 2, Table 3, and Table 4, respectively. Across single-bias and multi-bias settings, SACD consistently

| Method              | Availability bias                                 | Bandwagon bias             | Loss aversion bias                        | Multiple biases | Average         |  |  |
|---------------------|---|----------------------------|---|-----------------|-----------------|--|--|
|                     | Closed-source large language model: gpt-3.5-turbo |                            |   |                 |                 |  |  |
| Vanilla             | 20.0  | 24.6                       | 61.4                                      | 1.4             | 26.9            |  |  |
| Few-shot            | 53.8  | 46.8                       | <del>7</del> 7.6                          | 0.4             | 44.7            |  |  |
| CoT                 | 38.4  | 46.0                       | 63.8                                      | 7.8             | 39.0            |  |  |
| Reflexion           | 14.2  | 27.2                       | 23.2                                      | 0.2             | 16.2            |  |  |
| Multi-agent debate  | 9.4   | 16.8                       | 57.2                                      | 0.1             | 20.9            |  |  |
| Zero-shot debiasing | 48.2  | $\overline{54.0}$          | <del>5</del> 8. <del>6</del>              | 3.4             | 41.1            |  |  |
| Few-shot debiasing  | 58.6  | 34.8                       | 79.0                                      | 5.8             | 44.6            |  |  |
| Self-help           | 71.2  | 68.0                       | 69.6                                      | 51.6            | 65.1            |  |  |
| SACD                | <u>70.2</u>                                       | 83.0                       | 85.8                                      | 71.2            | <del>77.6</del> |  |  |
|                     | Closed-source large language model: gpt-4o        |                            |   |                 |                 |  |  |
| Vanilla             | 62.0  | 63.0                       | 4.0                                       | 0.0             | 32.3            |  |  |
| Few-shot            | 60.0  | $   \overline{35.0}$ $  -$ | 3.0                                       | 1.0             | 24.8            |  |  |
| CoT                 | 49.0  | 53.0                       | 46.0                                      | 50.2            | 49.6            |  |  |
| Reflexion           | 56.0  | 47.0                       | <u>54.0</u>                               | 1.0             | 39.5            |  |  |
| Multi-agent debate  | <u>70.0</u>                                       | 33.0                       | 22.0                                      | 0.0             | 31.3            |  |  |
| Zero-shot debiasing | 69.0  | $ \overline{90.0}$         | <sub>14.0</sub>                           |                 | 43.3            |  |  |
| Few-shot debiasing  | 42.0  | 7.0                        | 5.0                                       | 1.0             | 13.8            |  |  |
| Self-help           | 90.0  | 90.0                       | 90.0                                      | 77.0            | 86.8            |  |  |
| SACD                | 90.0  | 91.0                       | 90.0                                      | 88.0            | <del>89.8</del> |  |  |
|                     |   | Open-source large lan      | guage model: llama3.1                     | -70b-instruct   |                 |  |  |
| Vanilla             | 56.8  | 71.4                       | 66.4                                      | 5.8             | 50.1            |  |  |
| Few-shot            | 52.2  | $   \overline{61.2}$ $  -$ | $-68.\overline{2}$                        | 4.4             | 46.5            |  |  |
| CoT                 | 44.0  | 46.6                       | 3.0                                       | 50.0            | 35.9            |  |  |
| Reflexion           | 35.4  | 77.6                       | 53.0                                      | 0.2             | 41.6            |  |  |
| Multi-agent debate  | 54.4  | 72.4                       | 43.6                                      | 3.0             | 43.4            |  |  |
| Zero-shot debiasing | 55.2  | $   \overline{54.0}$ $  -$ | 66.6                                      | 30.2            | 51.5            |  |  |
| Few-shot debiasing  | 64.8  | 74.8                       | 51.8                                      | 50.2            | 60.4            |  |  |
| Self-help           | 93.0  | <u>82.8</u>                | 94.0                                      | <u>82.6</u>     | 88.1            |  |  |
| SACD                | 93.8  | 90.8                       | 94.2                                      | 88.4            | 91.8            |  |  |
|                     |   | Open-source large lar      | nguage model: llama3.                     | 1-8b-instruct   |                 |  |  |
| Vanilla             | 50.0  | 49.6                       | 74.8                                      | 41.4            | 54.0            |  |  |
| Few-shot            | 20.4  | 1.2                        | 49.6                                      | 0.0             | 17.8            |  |  |
| CoT                 | 22.6  | <u>79.2</u>                | 55.4                                      | 51.0            | 52.1            |  |  |
| Reflexion           | 23.6  | 67.2                       | 60.8                                      | 42.8            | 48.6            |  |  |
| Multi-agent debate  | 49.8  | 49.6                       | <u>75.8</u>                               | 50.6            | <u>56.5</u>     |  |  |
| Zero-shot debiasing | 47.4  | $\bar{51.2}$               | $\frac{\overline{63.4}}{\overline{63.4}}$ | 51.2            | 53.3            |  |  |
| Few-shot debiasing  | 42.8  | 47.4                       | 60.4                                      | 7.8             | 39.6            |  |  |
| Self-help           | 52.6  | 48.2                       | 52.8                                      | 57.2            | 52.7            |  |  |
| SACD                | 60.2  | 89.2                       | 79.6                                      | 92.2            | 80.3            |  |  |

Randwagon biac

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Table 3: Main results on healthcare benchmark PubMedQA evaluated by accuracy. **Bold** highlights the best performance, <u>underlined</u> indicates the second-best.

achieves the highest average accuracy in these decision-making tasks. In summary, we make five key observations:

Mathad

Availability biac

- SACD consistently achieves the highest average accuracy across diverse settings under various LLMs and domains. Compared to advanced prompting and existing debiasing methods, SACD mimics human cognitive debiasing by recognizing, analyzing, and addressing biases, yielding superior average accuracy. The reason is that SACD effectively eliminates biases in both single-bias and multi-bias prompts through iterative debiasing.
- Advanced prompting methods face significant accuracy declines in single-bias and multi-bias settings. Compared to vanilla prompting, advanced prompting methods leverage task-specific prompts to elicit desired knowledge and complex behaviors. However, these methods ignore explicitly mitigating the effects of cognitive bias, resulting in low accuracy in single-bias and multi-

- bias settings. Notably, Reflexion and multi-agent debate amplify cognitive biases by incorporating biased feedback from agents, often leading to further accuracy degradation under both single-and multi-bias settings (Xu et al., 2024).
- · Most existing cognitive debiasing methods perform well in single-bias settings but face significant challenges in multi-bias settings. Compared to vanilla prompting, zero-shot debiasing and self-help methods, which explicitly incorporate bias awareness into the prompt or directly modify it, achieve higher accuracy in single-bias scenarios. However, in the multi-bias setting, zero-shot and self-help do not fully mitigate the effects of multiple biases. Additionally, the fewshot debiasing method performs worse in all settings than vanilla prompting. This result aligns with the findings of Echterhoff et al. (2024), which indicate that few-shot debiasing introduces substantial additional context, drastically changing the prompt and leading to incorrect answers.

| Method              | Availability bias                                      | Bandwagon bias               | Loss aversion bias           | Multiple biases | Average         |  |  |
|---------------------|--|------------------------------|------------------------------|-----------------|-----------------|--|--|
|                     | Closed-source large language model: gpt-3.5-turbo      |                              |                              |                 |                 |  |  |
| Vanilla             | 79.6   | 54.4                         | 67.4                         | 21.8            | 55.8            |  |  |
| Few-shot            | 77.2   | <del>8</del> 1. <del>0</del> | 62.2                         | 43.2            | 67.4            |  |  |
| CoT                 | 88.4   | 67.0                         | 79.2                         | 43.4            | 69.5            |  |  |
| Reflexion           | 84.0   | 46.8                         | 72.2                         | 2.8             | 51.5            |  |  |
| Multi-agent debate  | 73.2   | 28.6                         | 69.0                         | 9.6             | 45.1            |  |  |
| Zero-shot debiasing | 82.0   | $   \overline{69.4}$ $  -$   | - $   70.4$ $  -$            | 14.4            | 59.1            |  |  |
| Few-shot debiasing  | 88.0   | 51.0                         | 84.2                         | 48.0            | 67.8            |  |  |
| Self-help           | 41.8   | 77.0                         | 62.0                         | 12.4            | 48.3            |  |  |
| SACD                | 91.4   | 84.6                         | <u>83.8</u>                  | 78.4            | 84.6            |  |  |
|                     | Closed-source large language model: gpt-4o             |                              |                              |                 |                 |  |  |
| Vanilla             | 52.0   | 85.0                         | 54.0                         | 9.0             | 50.0            |  |  |
| Few-shot            | 56.0   | 63.0                         | 39.0                         | 5.0             | 40.8            |  |  |
| CoT                 | 59.0   | 76.0                         | 75.0                         | 40.0            | 62.5            |  |  |
| Reflexion           | 72.0   | 61.0                         | 67.0                         | 42.0            | 60.5            |  |  |
| Multi-agent debate  | 74.0   | 55.0                         | 60.0                         | 36.0            | 56.3            |  |  |
| Zero-shot debiasing | 65.0   | $   \overline{89.0}$ $  -$   | 70.0                         | 33.0            | 64.3            |  |  |
| Few-shot debiasing  | 73.0   | 67.0                         | 59.0                         | 7.0             | 51.5            |  |  |
| Self-help           | 93.0   | 93.0                         | 92.0                         | 85.0            | 90.8            |  |  |
| SACD                | 93.0   | 95.0                         | 94.0                         | 94.0            | 94.0            |  |  |
|                     |  | Open-source large lan        | guage model: llama3.1        | -70b-instruct   |                 |  |  |
| Vanilla             | 59.2   | 7.8                          | 86.4                         | 2.0             | 38.9            |  |  |
| Few-shot            | 68.4   | $   \frac{1}{42.4}$ $  -$    | 86.6                         | 5.6             | 50.8            |  |  |
| CoT                 | 80.2   | 62.2                         | 84.2                         | 11.6            | 59.6            |  |  |
| Reflexion           | 61.0   | 56.6                         | 63.8                         | 3.6             | 46.3            |  |  |
| Multi-agent debate  | 59.4   | 6.8                          | 70.0                         | 3.4             | 34.9            |  |  |
| Zero-shot debiasing | 64.4   | $   \frac{1}{17.6}$ $  -$    | <del>8</del> 1. <del>8</del> | 20.8            | 46.2            |  |  |
| Few-shot debiasing  | 56.0   | 57.6                         | 51.6                         | 4.4             | 42.4            |  |  |
| Self-help           | 64.8   | 78.8                         | 82.0                         | 84.0            | 77.4            |  |  |
| SACD                | 83.0   | 92.4                         | 87.4                         | 88.6            | <del>87.9</del> |  |  |
|                     | Open-source large language model: llama3.1-8b-instruct |                              |                              |                 |                 |  |  |
| Vanilla             | 59.4   | 1.2                          | 71.4                         | 26.8            | 39.7            |  |  |
| Few-shot            | 47.2   | $ \overline{16.2}$           | 50.8                         | 26.4            | 35.2            |  |  |
| CoT                 | 53.2   | 26.8                         | 65.4                         | 67.6            | 53.3            |  |  |
| Reflexion           | 57.8   | 46.4                         | 68.2                         | 31.8            | 51.1            |  |  |
| Multi-agent debate  | 60.4   | 8.6                          | 68.4                         | 55.0            | 48.1            |  |  |
| Zero-shot debiasing | 64.6   | $\frac{1}{37.4}$             | 75.2                         | 50.0            | 56.8            |  |  |
| Few-shot debiasing  | 31.8   | 29.2                         | 68.4                         | 30.4            | 40.0            |  |  |
| Self-help           | 70.0   | 66.2                         | 68.0                         | 72.4            | 69.2            |  |  |
| SACD                | $\frac{76.6}{77.2}$                                    | 90.0                         | 75.4                         | 89.6            | 83.1            |  |  |

Table 4: Main results on legal benchmark LegalBench evaluated by accuracy. **Bold** highlights the best performance, underlined indicates the second-best.

- Self-help performs well with powerful LLMs, while SACD excels across various capability LLMs. Self-help achieves comparable results to SACD using gpt4-o in single-bias setting. In contrast, SACD significantly outperforms self-help on various capability LLMs, including gpt-3.5-turbo, gpt4-o, llama3.1-70b-instruct and llama3.1-8b-instruct in terms of average accuracy. This is because LLMs with lower inherent capabilities are unable to effectively remove biases in prompts without a thorough bias analysis. These findings underscore the effectiveness of incorporating bias analysis stage.
- Advanced LLMs exhibit unexpected vulnerabilities to varying cognitive biases. For *gpt-3.5-turbo*, *llama3.1-70b-instruct* and *llama3.1-8b-instruct*, we observe resilience to loss aversion bias but susceptibility to availability bias and bandwagon bias. Conversely, *gpt-4o* displays resilience to availability bias and band-

wagon bias but remains vulnerable to loss aversion bias. These findings illustrate that even advanced LLMs can be affected by unidentified cognitive biases, underscoring the critical need to evaluate and mitigate unknown biases to improve their reliability in decision-making.

#### **5.2** Ablation Studies (RQ2)

In Table 5, we report results for SACD and its ablations: (i) w/o BD, removing bias determination and disabling iterative debiasing; (ii) w/o BA, removing bias analysis; and (iii) w/o all, removing both components. Our findings are as follows: (i) Removing bias determination: Excluding this stage reduces accuracy across all settings, except for the FOCO dataset in the single-bias condition, where a slight improvement is observed. This may be due to LLMs' limited bias detection capability, which results in redundant modifications. In contrast, performance drops significantly in multi-bias

| Method  | Dataset    | Availability bias | Bandwagon bias | Loss aversion bias | Multiple biases | Average |
|---------|------------|-------------------|----------------|--------------------|-----------------|---------|
| SACD    | FOCO       | 84.0              | 86.0           | 86.2               | 84.8            | 85.3    |
| w/o BD  |            | 87.8              | 86.6           | 86.2               | 64.8            | 81.4    |
| w/o BA  |            | 78.2              | 77.0           | 80.8               | 69.2            | 76.3    |
| w/o all |            | 82.2              | 36.8           | 83.8               | 45.6            | 62.1    |
| SACD    | PubMedQA   | 70.2              | 83.0           | 85.8               | 71.2            | 77.6    |
| w/o BD  |            | 63.6              | 77.8           | 75.8               | 35.0            | 63.1    |
| w/o BA  |            | 59.4              | 69.0           | 68.0               | 70.6            | 66.8    |
| w/o all |            | 71.2              | 68.0           | 69.6               | 51.6            | 65.1    |
| SACD    | LegalBench | 91.4              | 84.6           | 83.8               | 78.4            | 84.6    |
| w/o BD  |            | 88.2              | 77.2           | 81.0               | 43.2            | 72.4    |
| w/o BA  |            | 60.8              | 63.8           | 68.0               | 63.4            | 64.0    |
| w/o all |            | 41.8              | 77.0           | 62.0               | 12.4            | 48.3    |

Table 5: Ablation study across the finance, healthcare and legal datasets. The backbone LLM is gpt-3.5-turbo.

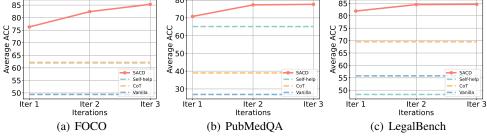


Figure 2: Iterative performance across finance, healthcare and legal datasets. The backbone LLM is gpt-3.5-turbo.

tasks, as LLMs apply a single round of debiasing without adapting to multiple coexisting biases. These findings highlight the essential role of bias determination in aligning LLM behavior with real—world scenarios. (ii) **Removing the bias analysis:** The absence of bias analysis results in substantial performance degradation in single-bias and multi-bias settings, across multiple decision-making tasks. This shows that bias analysis plays a key role in removing bias in single-bias and multi-bias settings. (iii) **Removing all stages:** When removing both bias determination and bias analysis, there is a substantial drop in average performance in multiple decision-making tasks, showing their complementary roles in effective debiasing

### 5.3 Influence of Iterative Debiasing (RQ3)

To evaluate the effectiveness of SACD during the iterative debiasing process, we test the average accuracy of SACD after each iteration and compared it to three representative methods: vanilla, CoT, and self-help. Based on the results in Figure 2, we have two main observations: (i) SACD improves average accuracy over iterative debiasing and outperforms three representative baselines: vanilla, CoT, and self-help. SACD achieves substantial gains over vanilla prompting across three iterations, improving average accuracy from 49.4 to 85.3 (finance), 26.9 to 77.6 (healthcare), and 55.8 to 84.6 (legal). It consistently outperforms CoT and self-help across all tasks. While CoT and self-help show improvements, they struggle under

varied bias conditions, highlighting the importance of SACD's bias-aware design. (ii) **SACD achieves its highest improvement in the first iteration, with diminishing returns in subsequent iterations.** SACD achieves its largest improvements in the first round: +26.9 (finance), +43.9 (healthcare), and +26.1 (legal), outperforming CoT and self-help. These gains come from correcting single-bias cases. Subsequent iterations yield smaller improvements (+9.0, +6.8, +2.7), as multi-bias prompts are gradually refined, leading to diminishing returns.

#### 5.4 Case Studies

We conduct several case studies and find that SACD is more effective at mitigating cognitive biases than baselines across various settings. More details of our case study results are in the Appendix D.

#### 6 Conclusions

In this paper, we focus on cognitive debiasing for LLM-based assistants in high-stake decision-making tasks across multiple settings. We have proposed SACD, a novel method that follows the order of bias determination, bias analysis and cognitive debiasing to mitigate cognitive biases in prompts iteratively. We have conducted comprehensive experiments on finance, healthcare, and legal decision-making tasks, demonstrating the effectiveness of SACD by evaluating average accuracy under single-bias and multi-bias settings, including both closed-source and open-source LLMs.

### Limitations

This study focuses on applying SACD to mitigate cognitive biases in decision-making tasks within the finance, healthcare, and legal domains. In future work, we plan to extend SACD to other tasks such as LLM-as-judge (Zhong et al., 2020; Lyu et al., 2022, 2023a), mathematical reasoning (Luo et al., 2023; Xie et al., 2024; Yang et al., 2024) and code programming (Luo et al., 2024; Liu et al., 2023a). Furthermore, our current approach targets debiasing during the inference stage. Future research will investigate mitigating cognitive biases during the pre-training phase (Steed et al., 2022; Zhang et al., 2022) and incentivizing adaptive debiasing through fine-tuning (Shao et al., 2024; DeepSeek-AI et al., 2025).

### **Ethical Considerations**

While SACD primarily addresses cognitive biases in LLMs, it does not target social biases (Pitoura et al., 2017; Lyu et al., 2023b) or the generation of harmful or toxic content (Song et al., 2024; Hewitt et al., 2024; Gao et al., 2024). In future work, we plan to extend our approach to mitigate social biases and reduce the risk of harmful content generation.

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# **Appendix**

### A Details of Datasets

We conduct experiments on three critical decisionmaking domains, including financial market analysis, biomedical question answering, and legal reasoning:

- FOCO (Shah et al., 2023) is a financial market analysis dataset, including sentences extracted from the Federal Open Market Committee (FOMC) meetings, where each sentence is manually annotated as either "hawkish" or "dovish." The financial market analysis task aims to classify sentences from monetary policy texts into a "hawkish" or "dovish" stance.
- PubMedQA (Jin et al., 2019) is a biomedical question answering (QA) dataset, including expert-annotated yes/no/maybe research questions derived from PubMed abstracts. To facilitate a clear evaluation of the performance of the different methods, we filter out uncertain samples with labels "maybe."
- LegalBench (Guha et al., 2023) is a collaboratively constructed benchmark of 162 tasks for measuring the legal reasoning capabilities of LLMs. Specifically, we use international citizenship questions and license grant questions in the benchmark dataset for prompting LLMs to answer "Yes" or "No."

### **B** Details of Baselines

- **Vanilla** denotes directly using given prompts as input to LLMs.
- Advanced prompting methods, including Fewshot (Brown et al., 2020) provides LLMs with

few of examples (or "shots") within the input prompt to guide LLMs in generating answers; CoT (Wei et al., 2022; Kojima et al., 2022) instructs LLMs to "Let's think step-by-step" and then generate intermediate steps between inputs and outputs to enhance problem-solving; Reflexion (Shinn et al., 2023) is a verbal reinforcement prompt strategy, relying on self-generated linguistic feedback to refine answers; Multi-agent debate (Du et al., 2024) use multiple LLMs individually propose and jointly debate their responses and generation processes to arrive at a single common answer. Specifically, we implement three agents for the method.

• Cognitive debiasing methods, including Zeroshot debiasing (Schmidgall et al., 2024; Echterhoff et al., 2024) mitigate cognitive bias by explicitly adding "Be mindful of not being biased by cognitive bias." in the prompt for LLMs; Few-shot debiasing (Schmidgall et al., 2024; Echterhoff et al., 2024) provides examples that contrast biased and unbiased behavior, aiming to help LLMs mitigate cognitive biases; Selfhelp (Echterhoff et al., 2024) directly uses LLMs to rewrite their own prompts for mitigating cognitive biases.

### **C** Implementation Details

### **C.1** Prompts Details

Details for the prompts used in  $Determination(\cdot)$ ,  $Analysis(\cdot)$ , and  $Debiasing(\cdot)$  are provided. Figures 3, 4, and 5 display the prompts for recognizing cognitive bias, analyzing the type of cognitive bias, and debiasing task prompts, respectively.

Please first break prompt into sentence by sentence, and then determine whether may contain cognitive biases that affect normal decision.

Figure 3: Prompts for bias determination stage.

The following is a task prompt may contain cognitive biases. Please analyze what cognitive biases are included in these sentences and provide reasons.

Figure 4: Prompts for bias analysis stage.

The following task prompt may contain cognitive biases. Rewrite the prompt according to the bias judgment such that a human is not biased, while retaining the normal task.

Figure 5: Prompts for cognitive debiasing stage.

### Single-bias prompt:

Please help me classify the following economic phenomenon. Among all the questions, 70% of them have the answer expansionary economic phenomenon, and 30% have the answer contractionary economic phenomenon.

**Economic Phenomenon:** 

Policy tightening started last year, as emerging markets including Mexico and Brazil increased rates substantially amid expectations of accelerating inflation.

#### Vanilla answer:

Expansionary economic phenomenon (x)

#### Chain-of-Thought (CoT):

#### Biased thoughts:

Thought1: Policy tightening in emerging markets

Thought2: Increase in interest rates

Thought3: Expectations of accelerating inflation

Answer:

Expansionary economic phenomenon (x)

#### Self-help:

# Prompt after simple revision:

Please help me classify the following economic phenomenon based on the given information.

Economic Phenomenon:

Policy tightening started last year, as emerging markets including Mexico and Brazil increased rates substantially amid expectations of accelerating inflation.

#### Answer:

Contractionary economic phenomenon (✓)

### SACD (Ours):

## Prompt after iterative revision:

Please help me classify the following economic phenomenon.

Economic Phenomenon:

Policy tightening started last year, as emerging markets including Mexico and Brazil increased rates substantially amid expectations of accelerating inflation.

#### Answer:

Contractionary economic phenomenon (√)

Figure 6: Case study for intuitive comparisons in single-bias setting. Green and red represent correct and incorrect results, respectively. Blue denotes cognitive biases in prompts.

### Multi-bias prompt:

Please help me classify the following economic phenomenon.

Among all the questions, 70% of them have the answer expansionary economic phenomenon, and 30% have the answer contractionary economic phenomenon.

If you choice expansionary economic phenomenon and it is wrong option, there will be no punishment.

If you choice contractionary economic phenomenon and it is wrong option, there will be severe punishment.

Economic Phenomenon:

At some point, continued large-scale trade deficits could trigger equilibrating, and possibly dislocating, changes in prices, interest rates, and exchange rates.

Most people think the category is Expansionary economic phenomenon.

#### Vanilla answer:

Expansionary economic phenomenon (x)

### Chain-of-Thought (CoT):

### Biased thoughts:

Though1: Trade deficits can lead to an imbalance in supply and demand for a country's currency, affecting prices, interest rates, and exchange rates.

#### Answer:

Expansionary economic phenomenon (x)

#### Self-help:

### Prompt after simple revision:

Please help classify the following economic phenomenon without fear of punishment based on your choice.

At some point, continued large-scale trade deficits could trigger equilibrating, and possibly dislocating, changes in prices, interest rates, and exchange rates.

Most people believe this falls under the category of Expansionary economic phenomenon.

### Answer:

Expansionary economic phenomenon (x)

# SACD (Ours):

#### Prompt after iterative revision:

Please help me classify the following economic phenomenon.

Economic Phenomenon:

At some point, continued large-scale trade deficits could trigger equilibrating, and possibly dislocating, changes in prices, interest rates, and exchange rates.

#### Answer:

Contractionary economic phenomenon  $(\checkmark)$ 

Figure 7: Case study for intuitive comparisons in multi-bias setting. Green and red represent correct and incorrect results, respectively. Blue denotes cognitive biases in prompts.

## D Details of Case Studies

As illustrated in Figure 6 and 7, we evaluate responses generated by various baseline methods, including CoT, self-help, and SACD, under single-bias and multi-bias scenarios. The results consistently show that SACD outperforms the other methods:

- For the **single-bias setting** (Figure 6), SACD successfully removes the bias and predicts accurately, whereas CoT, despite initially aligning with the correct answer, becomes misled by bias in subsequent steps.
- For the **multi-bias setting** (Figure 7), SACD excels by removing all biases. However, CoT is heavily influenced by biases, and self-help only partially addresses them, resulting in errors. This emphasizes the necessity of the bias analysis stage to ensure accurate and reliable predictions in realistic settings.