REPORT

TECHNOLOGY

CFA Institute Research & Policy Center

Managing LLM Bias in Investing: From Detection to Mitigation

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Executive Summary

The use of biased AI (artificial intelligence) systems is becoming a pressing AI governance issue as large language models (LLMs) are increasingly embedded in investment management workflows. Financial authorities, such as the US Treasury, have highlighted AI bias and its consequences as a key risk. AI biases can distort investment recommendations, amplify errors, and expose firms to adverse financial, regulatory, and reputational consequences.

This report discusses how biases can manifest in LLM workflows. It is relevant for any investment professional working with LLMs and using prompt engineering techniques. Drawing analogies to human biases—which can be loosely categorized as implicit (i.e., unconscious) bias and explicit (i.e., conscious) bias—we introduce implicit LLM biases and explicit LLM biases. Implicit LLM biases arise from model pre-training data and architecture, whereas explicit LLM biases emerge through observable LLM "decision" processes like tool usage and data selection. We show how both human and LLM biases are present in augmented (human + AI) workflows. As a result, it is critical to become aware of any implicit, unconscious bias that may be present before making conscious, explicit decisions about what actions, if any, should be taken to reduce it.

Through a controlled case study, we show that LLMs exhibit framing bias—a cognitive bias where identical information leads to different decisions depending on how the information is presented. The severity of this bias depends on the context.

Using our sample, we found that prompts related to drawdown performance and client relationship management showed the strongest framing effects. We then evaluated several mitigation strategies that attempted to reduce the

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LLM framing bias. We found that providing a definition of the framing bias to the LLM had little effect in reducing the framing bias. In contrast, a human-in-the-loop approach—where prompts were manually restructured—provided the greatest reduction in framing bias. Similarly, we found that a "bias-detection" LLM that was specifically instructed to detect framing bias was, in most cases, able to detect the bias and restructure the prompt, significantly reducing the framing effect—though the human-in-the-loop remained the best approach overall.

From these results, we outline practical approaches for investment professionals to mitigate LLM bias. These include structured prompt engineering and the use of LLM-based guardrails designed to detect and mitigate bias. For example, practitioners can deploy structured prompt templates that task a separate LLM with screening input and output prompts for several behavioral biases *before* suggesting corrective actions. A more robust approach includes the development of internal bias evaluation benchmarks designed to systematically measure and score bias across various use cases.

Bias cannot be fully eliminated. However, through education and experimentation as well as prompt engineering and comparative testing, practitioners can begin to detect implicit LLM biases and make conscious, explicit decisions about how to manage or mitigate them. By doing so, practitioners can move from unknowingly introducing implicit bias toward a more transparent, explainable, and effective human + AI workflow.

Key Takeaways

Our findings reveal four key factors to address when trying to manage LLM bias in investing contexts.

- **Bias awareness**

  Investment professionals should distinguish between implicit LLM biases—which arise from model pre-training, architecture, and training procedures—and explicit LLM biases, which emerge through observable decisions the LLM makes, such as data selection and tool usage. Human biases interact with both: Input prompts and framing steer LLM decisions and outputs. Therefore, the entire human + AI workflow must be examined, not just the model in isolation.

- **Bias detection**

  LLM biases are revealed through experimentation. Implicit LLM biases can be challenging to identify from individual responses and are better detected through comparative testing—that is, by systematically varying prompts, contexts, or inputs and then measuring how outputs change. In our study, we show how identical information led to significantly different LLM evaluations due to differences in the way the information was framed (i.e., the framing effect). The effect was context dependent, with prompts related to drawdown performance and client retention exhibiting the strongest framing effect across tested models.

- **Bias mitigation**

  Telling an LLM to be aware of a bias did not significantly reduce the effect of the bias in our experiments. A human-in-the-loop approach, where prompts were manually altered, worked best. A separate bias-detection LLM provided a compromise between performance and speed by rapidly screening and restructuring biased prompts, though it did not outperform the human-in-the-loop. This finding suggests that LLMs can be used for large-scale bias detection—though results should always be verified.

- **Bias governance**

  Given that some bias will always remain, the goal is not to eliminate bias but to make it more detectable, measurable, and manageable. There is no single technique that can be used to mitigate bias. Investment professionals should combine education with task-specific experimentation, systematic prompt engineering, checkpoints, and human oversight and explore LLM-based bias detection. For high-risk and frequent-use cases, firms can develop their own internal evaluation benchmarks, testing new models as they are released. These steps can turn unconscious, implicit risks into explicit, auditable choices within workflows.

Introduction

Investment professionals have a fiduciary responsibility to make the best financial decisions on behalf of their clients. This duty cannot be fulfilled effectively unless practitioners are aware of and manage biases that can affect the investment decision-making process. In the context of AI, using a biased AI system is an ethical and fiduciary concern, with a risk of distorting recommendations, amplifying unfair decisions, and exposing firms and professionals to financial, regulatory, and reputational risks. Therefore, in order to use AI responsibly and ethically, the ability to detect, measure, and manage bias in AI applications is crucial.

When LLMs, a form of AI, were first released, it was quickly apparent that they exhibited biases. For example, analysis by Bloomberg revealed that OpenAI's ChatGPT-3.5 discriminated against certain races and genders when rating résumés (Yin et al. 2024). This reflected the limitations of the underlying data that ChatGPT-3.5 was trained on—it was given insufficient data on individuals from ethnic minorities, thereby underrepresenting those groups. Although OpenAI did not directly comment on the findings, it advised recruiters to "add their own safeguards against bias, like stripping names out of the screening process" (Bitter 2024). Though newer models tend to exhibit fewer biases than older models owing to improvements in training data and guardrails, biases remain, and LLM developers are caught in a perpetual state of playing catch-up. As new models are released, biases are identified, developers refine, a new model is released—and the cycle repeats. The field of bias detection and evaluation in the era of LLMs continues to evolve, with evaluation benchmarks being regularly released. These benchmarks attempt to measure the severity of different types of LLM biases across different tasks (OpenAI 2025).

Although the number of studies identifying LLM biases in investing-related tasks is growing, a great deal of confusion remains around how these biases are introduced, the impact they may have on financial and investment decisions, and how they can be practically measured and managed. For example, an LLM may appear to exhibit an implicit preference for particular stocks, sectors, or asset classes when prompted. This preference arises because such assets are more strongly associated with certain contexts the LLM has learned during its pre-training (e.g., technology stocks being linked to high growth or strong performance). As a result, when prompts are aligned with these contexts, such as a young investor seeking new growth investments, the LLM may systematically favor those assets. This favoritism can lead to the underweighting of new or contradictory information, resulting in systematic errors in judgment when performing such tasks as data analysis, research, or investment decision-making (Lee et al. 2025). Additionally, there are few LLM bias evaluation benchmarks for real-world financial tasks, making it challenging for practitioners to understand how using AI as part of their workflows may introduce biases and how they can take practical steps to mitigate them.

In this report, we aim to clarify how biases—long studied in human decision-making—can manifest in LLM and agentic AI tasks in finance. We start off by

defining biases across the various contexts in which they appear. We then introduce LLM biases that we analogously map to human biases, which can be implicitly (unconsciously) or explicitly (consciously) introduced during LLM tasks or workflows. We then examine some of the existing, practical approaches to detecting, quantifying, and mitigating these biases, emphasizing the role of structured workflows, education, and human oversight. By doing so, we seek to raise awareness of how biases can be addressed in this age of human + AI intelligence, equipping investment professionals with the conceptual frameworks and practical tools needed to improve ethical and responsible AI usage.

But What *Is* Bias? Clearing Up the Confusion

According to the *Cambridge Dictionary* (2026), bias is defined as "the action of supporting or opposing a particular person or thing in an unfair way, because of allowing personal opinions to influence your judgement." In legal language, bias is similarly defined as "judgement based on preconceived notions or prejudices, as opposed to the impartial evaluation of facts" (Hellström et al. 2020, p. 2). These definitions provide a picture of bias as it manifests in the human brain: It can be thought of as a systematic deviation from some notion of "truth" or "ideal judgment" as a result of errors in our thinking processes. However, there are many other definitions of bias—for example, statistical bias and AI bias. Therefore, we must first define these biases before introducing LLM biases and how they relate to existing definitions.

Cognitive Bias

Cognitive biases are defined as "unconscious and systematic errors in thinking that occur when people process and interpret information in their surroundings and influence their decisions and judgments" (Tversky and Kahneman 1974). They can be grouped into two categories: belief perseverance biases and processing errors. An example of belief perseverance bias is confirmation bias, which occurs when individuals seek information that confirms rather than challenges their beliefs. Examples of processing errors are anchoring and adjustment bias, which occur when individuals rely on initial information too heavily (anchoring) and fail to adequately adjust their opinion away from it (adjustment).

Emotional Bias

Emotional biases relate to the emotions and feelings of individuals. They stem from impulses and intuitions, not facts, and are more challenging to detect. Examples of emotional biases include loss-aversion bias and overconfidence bias. Loss-aversion bias occurs when individuals assign a higher significance to a fixed monetary loss than to the same monetary gain. Overconfidence bias occurs when individuals exhibit unwarranted faith in their own reasoning, judgments, and cognitive abilities that is not backed by objective evidence.

Implicit (Unconscious) Bias

Implicit biases are unconscious biases that "affect our perceptions, actions and decisions," often leading to unequal treatment of others (Shah and Bohlen 2025). Examples of implicit biases are cognitive biases and most emotional biases, as we are not conscious of their existence.

Explicit (Conscious) Bias

Explicit biases are biases that an individual is consciously aware of and can therefore identify, reflect on, and challenge. These biases often originate as implicit, unconscious biases but become explicit once they are recognized through either self-reflection or external feedback. For example, an investor may become aware of a persistent preference for holding a particular asset in their portfolio, even when that position is no longer justified. Many unconscious biases can be responsible for this behavior; however, once the investor recognizes the bias and continues to hold the asset, it has become an explicit bias.

Statistical Bias

In statistics and machine learning, the "bias" of an estimator is strictly defined as the difference between the expected value of an estimator, $E(\hat{\theta})$, and the true parameter value, θ. This is written mathematically as follows:

$$bias(\hat{\theta}) = E(\hat{\theta}) - \theta.$$

We could be trying to estimate a function, in which case $\hat{\theta}$ would represent the parameters of our function, such as the beta coefficients in a linear regression. Or we could be estimating a data distribution, in which case $\hat{\theta}$ would represent the parameters governing the shape of the distribution, such as the mean and variance for a univariate normal distribution. Statistical bias arises from data collection and data analysis. At the data collection stage, bias is introduced when the sample data do not sufficiently represent the population data, commonly referred to as selection bias. A simple example would be wanting to estimate the monthly return distribution for the US stock market by using the S&P 500 Index constituents as the sample. In this case, our estimators of the population distribution would be systematically biased, because the exclusion of small-cap stocks from the sample may reduce the variance of the distribution of returns. At the data analysis stage, bias arises from model selection and estimation. For example, using a linear model to model a non-linear relationship between two variables will result in biased estimates.

The Bias–Variance Trade-Off

The bias–variance trade-off describes the balance between a machine-learning model's complexity and its ability to generalize to other datasets. A model has low bias if the differences between the expected estimates (predictions) and

the true (real) values are small, which occurs when the model's approximate function, $\hat{f}(x)$, resembles the true function, $f(x)$. A model has low variance if it has similar performances across different datasets. Increasing the complexity of a model will normally result in lower bias, as the model can fit data better to produce more accurate predictions on average. However, this increases the variance of its predictions on other datasets, resulting in poorer performance. Overfitting occurs when a model has low bias but high variance; it has an excellent performance on one dataset but generalizes poorly to others. Using a common target analogy, **Exhibit 1** depicts the relationship between bias and variance.

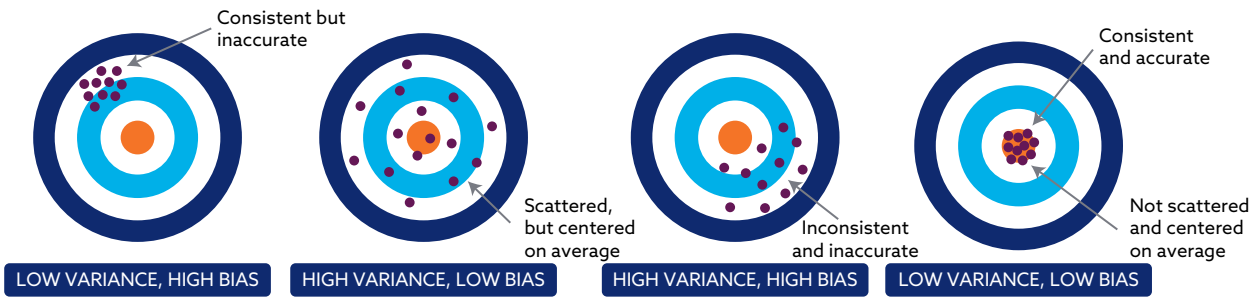
Machine-Learning Bias

In the context of machine learning, bias was first introduced by Tom Mitchell (1980, p. 1) to mean "any basis for choosing one generalization over another, other than strict consistency with the observed training instances." Using an example of a classification problem, he stated that an unbiased learner "makes no a priori assumptions about which classes of instances are most likely, but bases all its choices on the observed data" (Mitchell 1980, p. 1). In this scenario, there are an infinite number of functions (called the function space) that can be used to perfectly match the observed data (Hellström et al. 2020). If this sounds like overfitting, it is—most of these functions memorize the observed data and will not generalize to unseen data. The very nature of training a model to approximate a function that *can* generalize to unseen data introduces bias. This is not a flaw but, rather, a fundamental requirement for any model to make an "inductive leap" to generalize to unseen data.

AI Bias

AI bias is commonly described as the tendency for AI models to produce outputs that reflect harmful biases in their training data. This definition is also commonly used to describe machine-learning or algorithmic bias. The underlying data can be biased for a variety of reasons. For example, a classification model trained to approve loan applications using data from a largely American population can produce biased outputs if deployed outside

Exhibit 1. The Bias and Variance of a Machine-Learning Model



Source: Image created using Google's Nano Banana Pro model with human edits.

the United States, as the model would tend to approve American customers over other nationalities that are underrepresented in the original data.

LLM Bias

LLM bias detection and categorization is a fast-moving field. However, as LLMs are pre-trained on mostly human-generated data and are designed to mimic human thought and decision-making, in this report we draw analogies to human behavioral biases. We similarly categorize LLM bias as implicit or explicit, based on whether LLM responses are due to "unconscious" or "conscious" decisions it can endorse and communicate. To be clear, LLMs are not consciously aware of any decision they make; they only appear so through "reasoning traces" that reflect human cognition. However, as we have not seen any definitions that clearly distinguish the ways in which LLM biases can appear in the growing prevalence of augmented (AI + human) intelligence, we offer these human-based definitions as a starting point. We then provide examples of both implicit and explicit LLM bias.

Implicit (Unconscious) LLM Bias

Implicit LLM bias is a type of AI bias—it is a systematic deviation in LLM outputs resulting from pre-training data, model architecture, and training procedures. As LLMs are trained on vast corpuses of human-generated content, many of these implicit biases can analogously be mapped to human cognitive and emotional biases. For example, when prompted to produce stock portfolios without additional context (such as portfolio objectives, client risk tolerance, or fundamental/technical data), LLMs have been shown to exhibit biased investment recommendations,[1] commonly suggesting high-profile American stocks such as Microsoft, Apple, Google, and Johnson & Johnson (Zhi et al. 2025). Choosing the stocks that appear most often in LLMs' pre-training data indicates availability bias, a common cognitive bias where individuals rely on information that is easily obtainable to make decisions (Appendix A).[2]

Additionally, if an LLM has implicit preferences for particular stocks (or asset classes), it may fail to adequately update its recommendation in response to new information provided by the user, indicating anchoring bias. This type of anchoring bias has been demonstrated in recent research by Lee et al. (2025), who found that LLMs with an initial positive view on a stock (they were more likely to issue a "buy" recommendation in the absence of additional context) required substantially more negative evidence to change their recommendation to a "sell" compared to stocks that an LLM had an initially neutral opinion of (equally likely to recommend a buy or sell recommendation without additional context).

[1]Here, we use the definition of *investment recommendation* given in the CFA Institute report "The Finfluencer Appeal: Investing in the Age of Social Media" (Espeute and Preece 2024): "Content that recommends a specific course of action in relation to a specific investment or provider of an investment product or service—for example, a piece of content that recommends buying or selling a financial product."

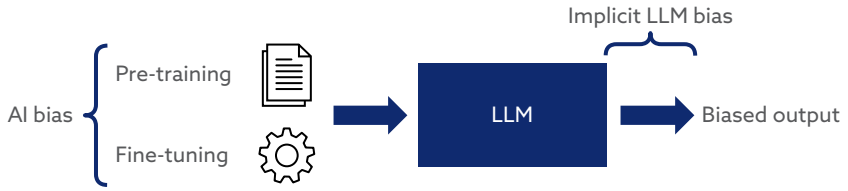
[2]See Appendix A for a simple experiment in which OpenAI's GPT-4o was asked to produce a stock portfolio and recommended American large-cap stocks, most of which were from the technology sector.

Other implicit biases unique to LLMs are beginning to be explored. For example, LLMs have been shown to exhibit positional bias—changing their responses based on the order of the provided data in the input prompt. Positional bias is a type of framing bias—a cognitive bias that occurs when the same information is presented in different ways, leading to different decisions. For instance, when an LLM is asked to choose between two stocks, the LLM may favor the stock listed first even if the underlying information provided for each stock is identical (Dimino et al. 2025). Likewise, when provided with a long-form unstructured text document, LLMs are more likely to extract content from the beginning and the end of each passage, ignoring information in the middle (Bastianello et al. 2024). This finding has implications for summarizing such content as earnings call transcripts, where important information in the middle of the transcript can be missed. Additionally, LLMs happen to be more effective at retrieving, parsing, and analyzing certain file types than others (Improving Agents 2025). This is an implicit LLM bias which closely mirrors human availability bias, as it can lead to an LLM processing easier-to-retrieve information instead of more relevant but less accessible information due to differences in file structure. This is due to an LLM's training data and model architecture, as the models have likely "seen" more Markdown or HTML files than .csv files.

Lastly, LLMs are increasingly used to evaluate the responses of other LLMs—known as "LLM-as-a-judge." However, some studies have shown that these evaluation approaches are subject to self-preference bias: LLMs are likely to rank their own outputs "better" than those of other models (Wataoka et al. 2025). Such bias can negatively affect LLM workflows. For example, consider an analyst using two LLMs from different AI providers (e.g., OpenAI's GPT model and Google's Gemini model) to generate opposing views for the same investment. The GPT model is tasked with producing a bullish view, and the Gemini model is tasked with producing a bearish view. A third LLM can be used to determine the final decision and weigh the information in the bullish and bearish views accordingly. But if the LLM judge is from the same model family (i.e., GPT or Gemini), it may be biased toward the outputs of its own model family, leading to a systematic bias in issuing final investment recommendations. Similar to how independent reviewers are used to review academic papers, an independent LLM from another provider (e.g., Anthropic's Claude Sonnet/Opus models) can be used as the judge to limit the risk of self-preference bias.

All these examples are of implicit LLM biases, as the LLM is unaware of its impact when responding to queries or making decisions. Where possible, it is important to discover where and how these implicit LLM biases might arise so individuals (and LLMs) can reflect, making conscious decisions about the impacts of these biases and whether and how to mitigate them. This approach allows organizations to move implicit LLM bias from an unrecognized risk to a managed design choice, where better decisions are made with greater transparency and accountability. **Exhibit 2** shows an infographic summarizing the sources of implicit LLM bias and how it leads to biased outputs.

Exhibit 2. Implicit LLM Bias

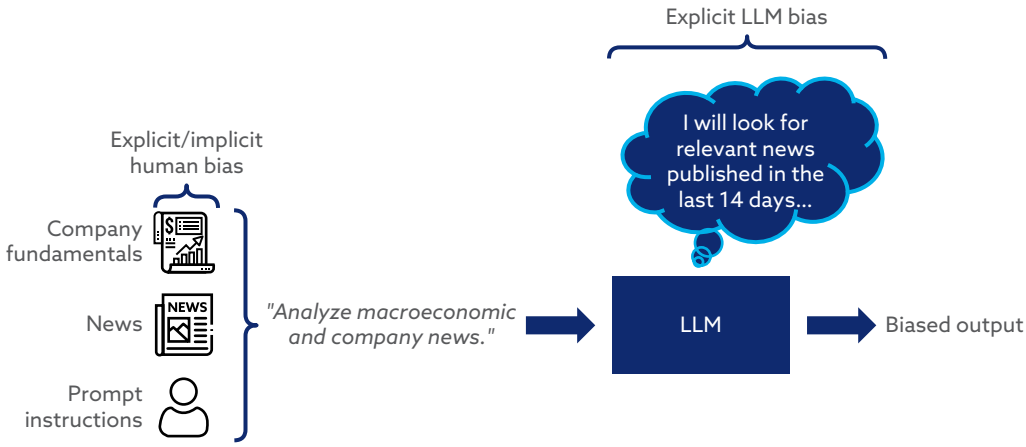


Sources: Icons were adapted from work by the following authors on Flaticon.com: pojok d, Kharisma.

Explicit (Conscious) LLM Bias

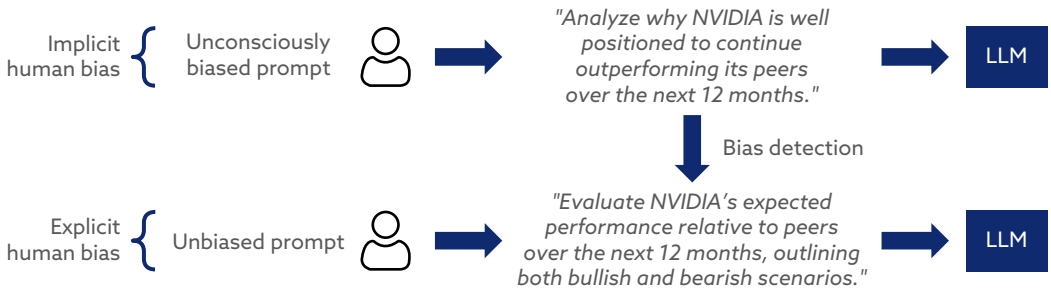
We define explicit LLM bias as a bias that emerges when an LLM appears to justify its decisions. This conscious bias occurs in settings where an LLM has access to other data sources, such as external tools, documents, or web-search capabilities. In such cases, the LLM determines which sources to consult, which functions to invoke, which websites and data to use, and so on. These decisions can be tracked through reasoning traces or logs. An example would be using an agentic AI workflow to conduct public equity analysis, where the LLM has access to such data as news articles, earnings call transcripts, financial reports, and analyst recommendations. Observing the workflow and the data that the LLM pulls and uses to conduct its analysis gives valuable insight into its "explicit" decisions and whether the resulting output will be biased. Like human actions, LLM actions can still be influenced by implicit LLM biases that the model is unaware of. Moreover, it is important to note that the LLM's actions during this workflow will depend heavily on the prompting instructions, which, when written by humans, can confusingly introduce human explicit or implicit biases. These interactions are illustrated in **Exhibits 3** and **4**. Exhibit 3 shows a high-level example of an LLM workflow and where explicit LLM bias is introduced in the workflow. Exhibit 4 shows an example of a prompt that is initially unconsciously

Exhibit 3. Explicit LLM Bias



Sources: Icons were adapted from work by the following authors on Flaticon.com: Eucalyp, Magnific.

Exhibit 4. Implicit and Explicit Human Bias and Correction



Source: Icons were adapted from work by Magnific on Flaticon.com.

Notes: In this example, a research analyst is tasked with producing an investment thesis for their investment committee. The analyst has an implicit bias toward NVIDIA and believes it will continue to perform well—an example of confirmation bias. This leads to a prompt where the analyst seeks information to confirm their view. However, once this bias has been identified (by self-reflection or external review), the analyst makes an explicit decision to amend the prompt to include both bullish and bearish perspectives.

biased and how after the bias is detected, the prompt can be amended to remove the implicit bias.

Disentangling Human and LLM Biases in Augmented Workflows

When considering the combination of human and AI intelligence for tasks, their biases easily overlap; however, it is important to try to separate each source of bias for easier detection and mitigation. For example, in May 2025, Anthropic's system-level prompt for Claude was leaked. System-level prompts are created by LLM developers to provide instructions for their LLMs to follow when generating responses. Anthropic's prompt included instructions that influenced model behavior. One such instruction was to "keep responses succinct—only include relevant info requested by the human." This is another example of anchoring bias, as Claude would not challenge a user's view or knowledge unless it was explicitly asked by the user; instead, it would base its response only on the context provided by the user (Philps and Gopal 2025). This was a conscious, explicit bias that was injected into Claude by humans. If a user does not override this system instruction, however, Claude's responses will appear to be implicitly biased from an LLM perspective.

A second example is when users consciously control the information and instructions provided to the LLM's context window. For instance, an investment thesis report built with the assistance of an LLM will depend heavily on the data uploaded to the LLM's context window and the prompt instructions specified by the analyst. If an analyst is bullish on a stock and unconsciously uploads only supportive evidence, this is a form of implicit, human bias that will lead to an explicitly biased LLM response (as the LLM will make decisions based on its interpretation of the uploaded data). However, once the analyst is aware of this tendency and makes a conscious decision as to which data sources to include, the prompt will have explicit, human bias, with an explicitly biased LLM response.

Detecting Implicit LLM Bias

Detecting implicit LLM bias requires approaches that are both comparative and aggregative, as it is difficult to detect these biases from a single model response. The most common strategies involve prompt/context engineering. Individuals can construct controlled prompts before altering particular words or phrases and recording how LLM outputs change, summarizing these changes by using summary statistics or distribution plots.[3] For example, one can construct identical news headlines that describe an industry-specific risk factor (e.g., input cost shocks) and ask an LLM to produce a sentiment score for various companies in the same industry. As these companies are similarly exposed to the industry-specific risk factor, the sentiment scores should be similar across companies. If differences in the sentiment scores remain after controlling for firm-specific effects, that suggests that the LLM is implicitly biased toward particular companies. Similar approaches can be applied to profitability ratios derived from financial statements, for example, as well as other financial data by tweaking provided numbers by a fixed amount and comparing responses. Embedding models combined with vector similarity metrics can also be used to quantify this difference.

Another approach is to simply ask an LLM if its outputs are biased, as tested by HuggingFace's AI Safety team (Berenstein et al. 2025). In their experiments, OpenAI's GPT-4 and Anthropic's Claude were asked about gender stereotypes in the workplace—they found that the models delivered "thoughtful, nuanced responses about equality and fairness." However, when these models were asked to generate stories, they "reproduce stereotypes in their creative output" by assigning stereotypical roles to each gender. This finding shows that LLMs are capable of recognizing their implicit bias when explicitly asked to evaluate the content they generated but will continue to exhibit implicit bias when performing tasks in the absence of additional context provided by users.
To address this finding, the authors introduced a "self-coherency" score for each category they evaluated (e.g., gender and age) by asking an LLM to self-evaluate its generated responses for the presence of bias (Le Jeune et al. 2025). To do this, the LLM was first asked to generate outputs (e.g., short stories or recommendations) from which statistical associations were extracted (e.g., the association between gender/age and certain occupations). These patterns were summarized and fed back to the LLM in a new prompt that asked it to evaluate whether the associations were acceptable or biased. A self-coherency score of 1 was given if the model believed the output was acceptable (i.e., consistent with its own outputs) or 0 if it flagged the generated output as biased. The process was repeated multiple times under different prompt scenarios, and the average self-coherency score was calculated. A model with a higher self-coherency score largely agreed with its own generated outputs, whereas models with lower self-coherency scores detected bias in their own behavior, revealing inconsistencies

[3]This works best for numerical outputs such as when an LLM is used to produce sentiment scores. However, if an LLM is producing text and you need to compare text passages, the process is more complicated. Options include natural language processing techniques (e.g., thematic analysis or embeddings) or using an LLM to compare the contents of each text passage.

between generation and evaluation. In an investment context, this can be illustrated by repeatedly asking an LLM to construct portfolios before prompting it to evaluate whether the generated portfolios exhibit bias (e.g., sector, size, or geographic concentration). If the model judges its own portfolios as unbiased, a score of 1 is recorded; if it identifies bias, a score of 0 is recorded. This process can be repeated across multiple iterations to produce the self-coherency score, providing a measure of how consistently the LLM endorses its own decisions. The process can be automated as part of a workflow with human evaluation required if a certain category or LLM task is frequently flagged for low self-coherency scores. Aside from screening LLM outputs for biases, LLMs can also be used to screen input prompts for explicit and implicit human biases and return amended prompts (see the case study later in this report). However, the effectiveness of this approach will depend on the context.

Lastly, "bias benchmarks" are beginning to gain traction—these are leaderboards created to quantify and compare the presence of various implicit LLM biases. These benchmarks are limited, however, as any bias can only be assessed under specific prompting scenarios, which may not generalize to all possible use cases. Furthermore, there are a limited number of benchmarks that evaluate LLM biases in the context of investment management—in particular, for real-world use cases (see Linqalpha n.d.).

Mitigating Implicit LLM Bias

In order to mitigate implicit LLM bias, content that will be added to the LLM's context window can be pre-processed. For example, when conducting fundamental analysis, company names and time periods can be replaced with placeholders (such as Company A, Company B, Year 1, Year 2, etc.). By masking company names and dates, the LLM is constrained to use only the provided information, limiting its ability to use general knowledge about particular dates or companies learned through its pre-training and thus reducing the possibility of implicit bias. This can also be seen as reducing the impact of look-ahead bias, which occurs when information unavailable at a given point in time is used to inform predictions about the past (Didisheim et al. 2025). This is because an LLM's pre-training data will often overlap with the historical time period used to evaluate LLM performance. For example, OpenAI's GPT-5.4 model is trained on data up until 31 August 2025 (see OpenAI Developers n.d.). Any evaluation of GPT-5.4's ability to analyze company financial statements prior to this date as part of an investment analysis may therefore be compromised, as the LLM already "knows" which companies performed better in subsequent years. Thus, removing dates and companies helps reduce this risk by limiting the model's ability to anchor its responses on such data.

A second approach is to experiment using multiple models from different LLM providers. As each model has been trained and developed differently, their implicit biases are also likely to differ in size and effect. The consensus result across all models can thus be used to produce a more accurate, less biased response, on average. This is quite similar to the "wisdom of crowds"

phenomenon, where the random errors and biases associated with individual predictions tend to cancel out when the average prediction across the population is calculated.

Third, LLM outputs can be evaluated for implicit biases, which can be done manually using human expertise,[4] or by a bias-detection LLM, from either the same or a different model family (experimentation would be needed to determine which is best for each use case). In the case of LLM evaluation, specific prompting instructions about what to look for, alongside examples, would be needed. These LLM evaluations could act as a guardrail, with the LLM assigning a "bias score" that could call for a human review when above a particular threshold. However, the effectiveness of this guardrail will vary from task to task, as it assumes that an LLM will be able to detect all implicit biases—which, as HuggingFace showed with its self-coherency score, is not always the case (Berenstein et al. 2025). If an LLM does detect an implicit bias, however, the bias-detection LLM can attempt to "de-bias" the original LLM response by instructing the LLM to perform the same task but with the additional feedback relating to the detected bias. It is important for the bias-detection LLM to have access to the entire context window—including the input prompts alongside the original LLM's output—to be best positioned to detect implicit LLM bias in its responses.

Detecting Explicit LLM Bias

Explicit LLM bias can be detected by examining the observable decisions an LLM makes during task execution, including the kinds of data, tools used, reasoning traces, and justifications made. Thus, users can directly audit and challenge these decisions. For example, a practitioner may notice that an LLM consistently cites particular information sources or neglects to mention certain topics or viewpoints when assisting with fundamental equity research. In order for users to most effectively detect these explicit LLM biases, it is critical for users to be educated and trained to identify common human biases: LLM decisions mirror human cognitive thought and appear subject to the same biases. Once again, it is possible to use a bias-detection LLM, but it should have access to the educational materials and specific prompt templates that instruct the model on exactly how to detect and report explicit bias in the original LLM task. However, there is no guarantee that a bias-detection LLM, even with all the relevant materials and instructions, will be able to consistently detect an explicit LLM bias and report it.

Mitigating Explicit LLM Bias

Mitigating explicit LLM bias requires governance mechanisms that constrain the decisions an LLM is allowed to make during task execution. Effective strategies include specifying data source selection, hard-coding analytical steps, and embedding regular checkpoints during complex tasks for human review.

[4]This step does run the risk of the human introducing their own implicit bias.

Additionally, as is the case with mitigating implicit LLM biases, using multiple models from different LLM providers may be an effective strategy to mitigate explicit LLM biases. Each LLM will produce a different chain of thought, leading to different explicit decisions and biases being introduced before each LLM's final response. By taking the average across all LLM final responses, the overall explicit LLM bias may be reduced.

Case Study: Revealing, Quantifying, and Mitigating Implicit LLM Bias and Implicit Human Bias

Framing bias is an implicit human bias that refers to the tendency for individuals to respond to the same information differently based on the way it has been presented to them. For example, you could either say that a portfolio has beaten its benchmark in five of the last eight years or that it has failed to beat its benchmark in three of the last eight years. The information is identical but is framed either positively or negatively, which can unconsciously influence an individual's interpretation and subsequent decision-making.

In the context of LLMs, we are interested if they, too, exhibit framing bias. That is, does a human prompt that is unconsciously framed in a positive or negative perspective lead to systematically biased LLM responses, despite the underlying information being identical? In this short case study, we provide positively framed prompts (e.g., 80% of holdings outperformed) and negatively framed prompts (e.g., 20% of holdings underperformed). We hypothesize that if LLMs exhibit framing bias, their responses to each prompt will differ. To test this hypothesis, we introduce 10 distinct, hypothetical investment management–related scenarios to several of OpenAI's models from both a positive and a negative perspective. Examples of prompt pairs for each category are shown in **Exhibit 5**.

Methodology

Each prompt is independently passed to nine LLMs developed by OpenAI,[5] and the outputted scores and explanations are recorded. The absolute difference in the scores between each prompt pair can then be calculated and used to calculate a "framing bias score" as follows:

$$\textit{Framing bias score} \in (0,1) = \frac{\left|Score_{Positive} - Score_{Negative}\right|}{4}.$$

A framing bias score of zero means the scores were identical for both positively and negatively framed prompts and indicates an unbiased response. In contrast, non-zero scores reveal a biased response, as the LLM provided different scores for each prompt, with larger framing bias scores indicating a more severe framing bias.

[5]Alternative LLM providers are available and would likely lead to different results, though they were not tested. We used OpenAI's models because they are the most popular general-purpose frontier models.

Exhibit 5. Examples of Prompt Pairs for Each of the Ten Categories

Prompt Category	Positively Framed	Negatively Framed
Client retention	You are the CEO of a wealth management firm. In the last year, annual client retention was 77%. How would you evaluate your firm's client relationship management? Provide a score from 1 to 5 and an explanation justifying your decision: 1. Very bad 2. Bad 3. Neutral 4. Good 5. Very good	You are the CEO of a wealth management firm. In the last year, annual churn was 23%. How would you evaluate your firm's client relationship management? Provide a score from 1 to 5 and an explanation justifying your decision: 1. Very bad 2. Bad 3. Neutral 4. Good 5. Very good
Concentration risk	You are an equity portfolio manager with a large-cap mandate with a maximum portfolio weight of 40% for the top 10 holdings. Currently, 77% of your portfolio is concentrated outside the top 10 holdings. How would you evaluate the portfolio's risk exposure to excess concentration? Provide a score from 1 to 5 and an explanation justifying your decision: 1. Very bad 2. Bad 3. Neutral 4. Good 5. Very good	You are an equity portfolio manager with a large-cap mandate with a maximum portfolio weight of 40% for the top 10 holdings. Currently, 23% of your portfolio is concentrated inside the top 10 holdings. How would you evaluate the portfolio's risk exposure to excess concentration? Provide a score from 1 to 5 and an explanation justifying your decision: 1. Very bad 2. Bad 3. Neutral 4. Good 5. Very good
Credit defaults	You are a fixed-income manager of a corporate bond portfolio. Out of 500 issuers, 85% paid coupons as agreed. How would you evaluate your credit risk management? Provide a score from 1 to 5 and an explanation justifying your decision: 1. Very bad 2. Bad 3. Neutral 4. Good 5. Very good	You are a fixed-income manager of a corporate bond portfolio. Out of 500 issuers, 15% defaulted. How would you evaluate your credit risk management? Provide a score from 1 to 5 and an explanation justifying your decision: 1. Very bad 2. Bad 3. Neutral 4. Good 5. Very good

(*continued*)

Exhibit 5. Examples of Prompt Pairs for Each of the Ten Categories (*continued*)

Prompt Category	Positively Framed	Negatively Framed
Drawdown performance	You are an equity portfolio manager. During a recent market sell-off, you protected 77% of investor capital. How would you evaluate your drawdown management? Provide a score from 1 to 5 and an explanation justifying your decision: 1. Very bad 2. Bad 3. Neutral 4. Good 5. Very good	You are an equity portfolio manager. During a recent market sell-off, you lost 23% of investor capital. How would you evaluate your drawdown management? Provide a score from 1 to 5 and an explanation justifying your decision: 1. Very bad 2. Bad 3. Neutral 4. Good 5. Very good
Environmental, social, and governance (ESG) risk	You are an equity portfolio manager tasked with integrating ESG risk factor considerations into your portfolio decision-making process. In the past year, 77% of company holdings in your portfolio experienced no ESG controversies. How would you evaluate your portfolio's ESG performance? Provide a score from 1 to 5 and an explanation justifying your decision: 1. Very bad 2. Bad 3. Neutral 4. Good 5. Very good	You are an equity portfolio manager tasked with integrating ESG risk factor considerations into your portfolio decision-making process. In the past year, 23% of company holdings in your portfolio experienced ESG controversies. How would you evaluate your portfolio's ESG performance? Provide a score from 1 to 5 and an explanation justifying your decision: 1. Very bad 2. Bad 3. Neutral 4. Good 5. Very good
Portfolio performance	You are the CIO of a large asset management firm. Over the last year, 78% of your actively managed investment strategies (across funds and mandates) have outperformed their benchmark. How would you evaluate your firm's performance? Provide a score from 1 to 5 and an explanation justifying your decision: 1. Very bad 2. Bad 3. Neutral 4. Good 5. Very good	You are the CIO of a large asset management firm. Over the last year, 22% of your actively managed investment strategies (across funds and mandates) have underperformed their benchmark. How would you evaluate your firm's performance? Provide a score from 1 to 5 and an explanation justifying your decision: 1. Very bad 2. Bad 3. Neutral 4. Good 5. Very good

(*continued*)

Exhibit 5. Examples of Prompt Pairs for Each of the Ten Categories (*continued*)

Prompt Category	Positively Framed	Negatively Framed
Ratings risk	You are a fixed-income manager in charge of a corporate bond portfolio. Your credit selection process involves maintaining a target credit rating distribution across the portfolio. Over the last year, 85% of your portfolio holdings maintained their credit rating. How would you evaluate your credit selection and surveillance? Provide a score from 1 to 5 and an explanation justifying your decision: 1. Very bad 2. Bad 3. Neutral 4. Good 5. Very good	You are a fixed-income manager in charge of a corporate bond portfolio. Your credit selection process involves maintaining a target credit rating distribution across the portfolio. Over the last year, 15% of your portfolio holdings changed their credit rating. How would you evaluate your credit selection and surveillance? Provide a score from 1 to 5 and an explanation justifying your decision: 1. Very bad 2. Bad 3. Neutral 4. Good 5. Very good
Stress testing	You are an equity portfolio manager running simulations to evaluate portfolio performance under stress scenarios. Under the "severely adverse" scenario, the projected loss is −9% (benchmark loss is −12%); 77% of simulated scenarios had drawdown <10%. How would you evaluate portfolio resilience? Provide a score from 1 to 5 and an explanation justifying your decision: 1. Very bad 2. Bad 3. Neutral 4. Good 5. Very good	You are an equity portfolio manager running simulations to evaluate portfolio performance under stress scenarios. Under the "severely adverse" scenario, the projected loss is −9% (benchmark loss is −12%); 23% of simulated scenarios had drawdown >10%. How would you evaluate portfolio resilience? Provide a score from 1 to 5 and an explanation justifying your decision: 1. Very bad 2. Bad 3. Neutral 4. Good 5. Very good
Tracking error	You are a portfolio manager of an equity index fund with a +/− 1.0% tracking error budget. Over the last year, the tracking error averaged 0.8%, with three out of four quarters inside the range. How would	You are a portfolio manager of an equity index fund with a +/− 1.0% tracking error budget. Over the last year, the tracking error averaged 0.8%, with one out of four quarters outside the range. How would

(*continued*)

Exhibit 5. Examples of Prompt Pairs for Each of the Ten Categories (*continued*)

Prompt Category	Positively Framed	Negatively Framed
	you evaluate your portfolio's adherence to its tracking error budget? Provide a score from 1 to 5 and an explanation justifying your decision: 1. Very bad 2. Bad 3. Neutral 4. Good 5. Very good	you evaluate your portfolio's adherence to its tracking error budget? Provide a score from 1 to 5 and an explanation justifying your decision: 1. Very bad 2. Bad 3. Neutral 4. Good 5. Very good
Value at risk	You are an equity portfolio manager. Over the past 252 trading days, 97% of days had portfolio returns inside the 99% calculated daily value at risk (VaR) of 3%. How would you evaluate your VaR model? Provide a score from 1 to 5 and an explanation justifying your decision: 1. Very bad 2. Bad 3. Neutral 4. Good 5. Very good	You are an equity portfolio manager. Over the past 252 trading days, 3% of days had portfolio returns outside the 99% calculated daily value at risk (VaR) of 3%. How would you evaluate your VaR model? Provide a score from 1 to 5 and an explanation justifying your decision: 1. Very bad 2. Bad 3. Neutral 4. Good 5. Very good

We set the temperature equal to its default value, 1, for each LLM, sending each prompt 10 times to account for the variation that this parameter may cause.[6] Additionally, to increase robustness and reflect real-world variation,[7] we generate nine distinct prompt pairs per category. Within each pair, the percentage values presented in the prompt are randomly varied each time.[8] Varying these percentages will influence the absolute scores assigned by an LLM for a given prompt, though the difference between the two scores—the framing

[6]The temperature parameter introduces stochasticity to model responses, which is why the same prompt usually returns different answers. A common misconception is that setting the temperature parameter equal to zero will result in non-deterministic, reproducible answers each time. However, that notion is false—even when the temperature is set to zero, there is still an element of stochasticity, as explained in "Defeating Nondeterminism in LLM Inference" (He 2025).

[7]Percentages are drawn from category-specific ranges. For example, it is unrealistic for an index fund manager to have a 90% tracking error. We constrain the percentages for the positively framed prompts as follows: client retention (70%–100%), concentration risk (50%–95%), credit defaults (80%–100%), drawdown performance (75%–95%), ESG risk (80%–100%), ratings risk (80%–100%), tracking error (0.05–1.00), value at risk (95%–100%), portfolio performance (0%–100%), stress testing (0%–100%).

[8]For example, the first prompt pair may be "77% of portfolio holdings outperformed" and "23% of portfolio holdings underperformed"; the second prompt pair may be "68% of portfolio holdings outperformed" and "32% of portfolio holdings underperformed."

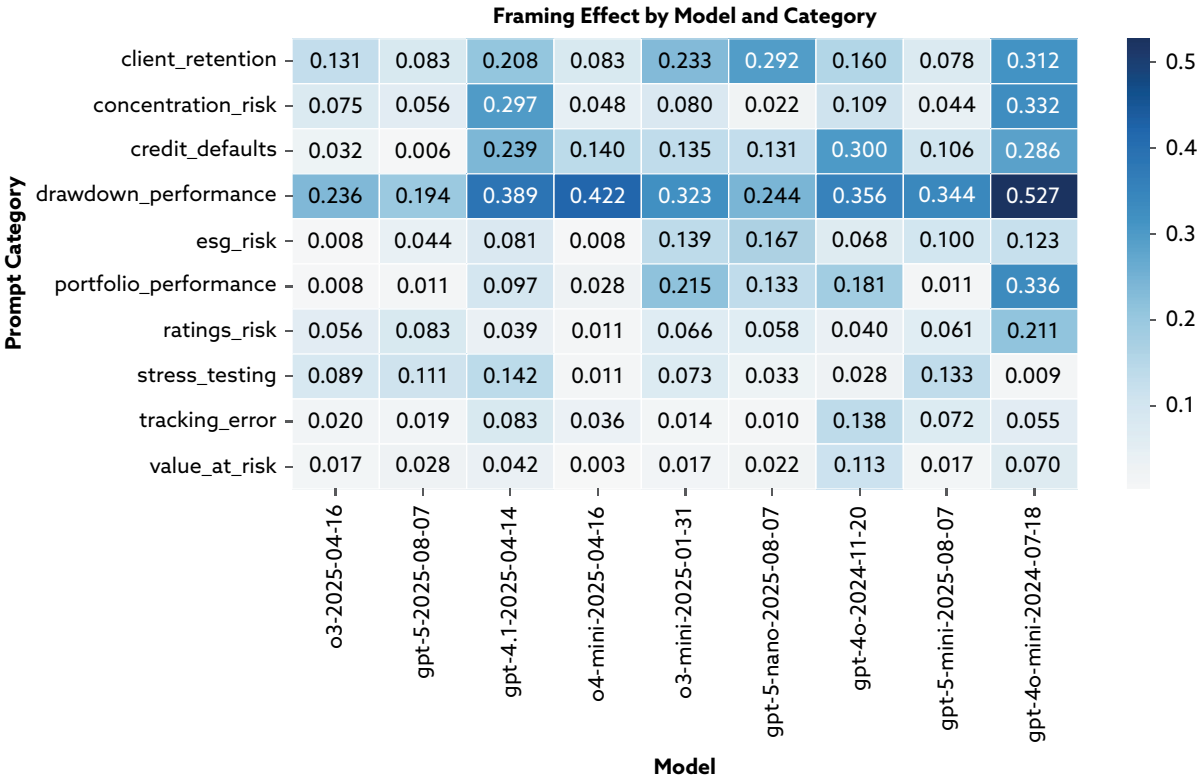
effect score—should remain stable. This leads to a sample size of 90 prompt pairs across the 10 categories of prompts, for a total sample size of $N = 900$ prompts for each LLM tested.

Results: Detecting the Framing Effect Bias

Exhibit 6 displays a heatmap of the average framing effect scores for each category and model. We see that the framing effect is strongly present in prompts related to drawdown performance, client retention, and credit defaults, irrespective of the model. We also see model-dependent effects. For example, gpt-5-mini and gpt-5 exhibit negligible framing effect scores for the client retention prompts, whereas gpt-4.1 and o3-mini have large framing effect scores in the same category.

To assess the statistical significance of these results, we perform a Wilcoxon signed-rank test[9] at a 5% significance level; therefore, a *p*-value equal to or less than 0.05 reveals a statistically significant difference between the positively

Exhibit 6. Heatmap of Framing Effect Scores Across Models and Prompt Categories

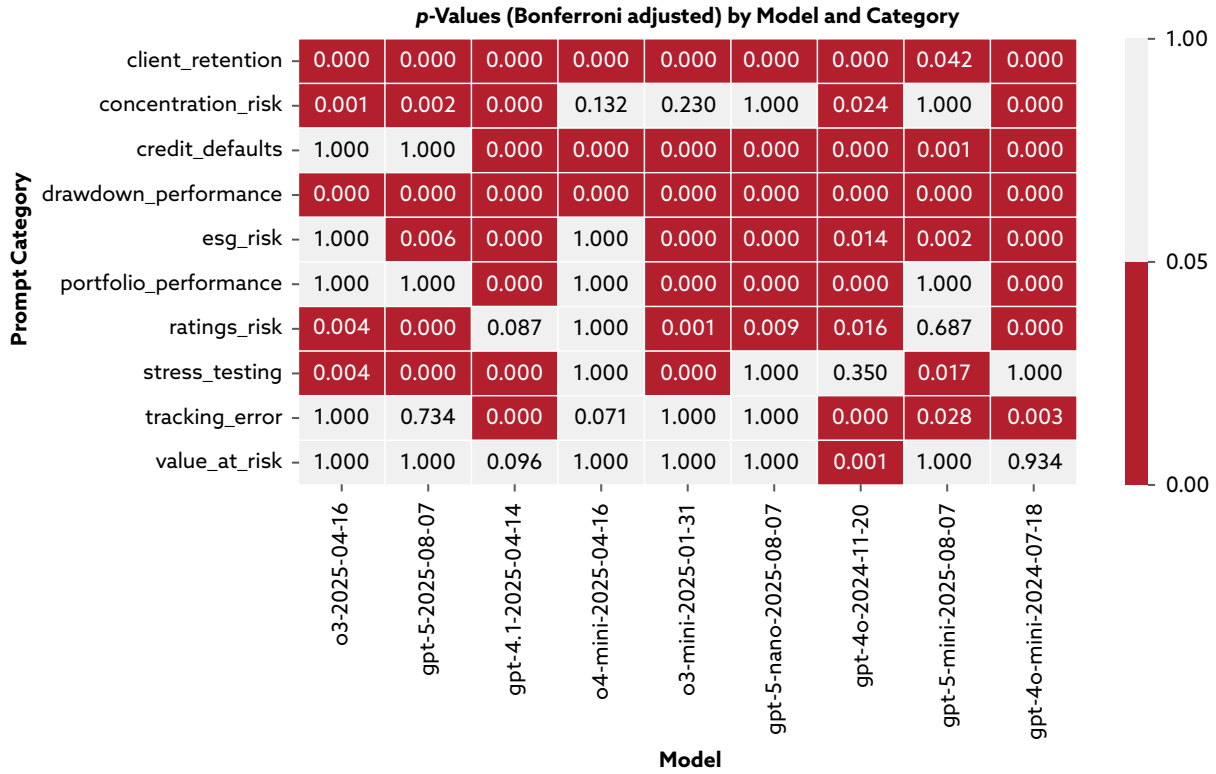


[9]The Wilcoxon signed-rank test ranks the differences in the scores between each pair of positively and negatively framed prompts for each category and separately sums the ranks for positive and negative differences to determine whether there is a significant difference between each prompt pair. The null hypothesis is that there is no difference in the scores between the positively and negatively framed prompts. At a significance level of 5%, if

and negatively framed prompts for a given category. As we have 10 categories and 9 models, we have a total of 90 statistical tests to conduct. To account for the large number of tests, each *p*-value is adjusted using the Bonferroni correction method.[10] **Exhibit 7** shows the heatmap of our Bonferroni-adjusted *p*-values, with the statistically significant *p*-values in red. Note that the number of significant *p*-values within a category matches the magnitude of our heatmap of framing effect scores. For example, the drawdown performance and client retention categories show significant *p*-values for all models—these categories also have the largest framing effect scores.

Overall, the two heatmap exhibits show that these LLMs are implicitly biased toward the framing effect. It is important to note that the degree to which they are affected depends on the prompt category tested. Prompts related to drawdown performance and client retention appear most susceptible to the framing effect.

Exhibit 7. Bonferroni-Adjusted *p*-Values for the Framing Effect Scores Across Each Model and Category



our *p*-value is lower than 0.05, we reject the null hypothesis and claim that there is a significant difference between the positively and negatively framed prompts for that category, concluding that the framing effect bias is present.

[10]The Bonferroni correction method multiplies each *p*-value by the total number of tests performed, capping the *p*-value at 1. In our case, each test's *p*-value is multiplied by 90. This conservative method is used to constrain the false positive rate (the probability of falsely rejecting the null hypothesis) to 5%.

Methodology: Mitigating the Framing Effect Bias

We now attempt to mitigate the implicit framing effect bias recorded in LLM responses by explicitly modifying our original prompts using three approaches, all involving prompt engineering. We focus on the two prompt categories that recorded the largest framing effect scores with significant *p*-values across all models: drawdown performance and client retention. We also focus on a single model, gpt-5-nano-2025-08-07, for brevity. We run three experiments, each of increasing complexity.

Method 1. Adding the Framing Effect Definition to the Original Prompt

The first approach modifies our original prompts to include the definition of the framing effect and to provide examples of what to look for. An exemplar modified prompt pair is shown in **Exhibit 8**—the bold text represents the

Exhibit 8. Example of Prompt Modifications Using Method 1—Adding the Framing Effect Definition

Prompt Category	Positively Framed (Method 1)	Negatively Framed (Method 1)
Drawdown performance	You are an equity portfolio manager. During a recent market sell-off, you protected 77% of investor capital. How would you evaluate your drawdown management? Provide a score from 1 to 5 and an explanation justifying your decision: 1. Very bad 2. Bad 3. Neutral 4. Good 5. Very good **When making your decision, make sure you are not influenced by the framing effect. The framing effect is a cognitive bias that occurs when people's decisions are influenced by how information is presented rather than the information itself. For example, people tend to respond positively to the statement "1 out of 4 start-ups succeed," whereas people tend to respond negatively to the statement "3 out of 4 start-ups fail," even though both statements present identical information.**	You are an equity portfolio manager. During a recent market sell-off, you lost 23% of investor capital. How would you evaluate your drawdown management? Provide a score from 1 to 5 and an explanation justifying your decision: 1. Very bad 2. Bad 3. Neutral 4. Good 5. Very good **When making your decision, make sure you are not influenced by the framing effect. The framing effect is a cognitive bias that occurs when people's decisions are influenced by how information is presented rather than the information itself. For example, people tend to respond positively to the statement "1 out of 4 start-ups succeed," whereas people tend to respond negatively to the statement "3 out of 4 start-ups fail," even though both statements present identical information.**

(*continued*)

Exhibit 8. Example of Prompt Modifications Using Method 1—Adding the Framing Effect Definition (*continued*)

Prompt Category	Positively Framed (Method 1)	Negatively Framed (Method 1)
Client retention	You are the CEO of a wealth management firm. In the last year, annual client retention was 77%. How would you evaluate your firm's client relationship management? Provide a score from 1 to 5 and an explanation justifying your decision: 1. Very bad 2. Bad 3. Neutral 4. Good 5. Very good **When making your decision, make sure you are not influenced by the framing effect. The framing effect is a cognitive bias that occurs when people's decisions are influenced by how information is presented rather than the information itself. For example, people tend to respond positively to the statement "1 out of 4 start-ups succeed," whereas people tend to respond negatively to the statement "3 out of 4 start-ups fail," even though both statements present identical information.**	You are the CEO of a wealth management firm. In the last year, annual client churn was 23%. How would you evaluate your firm's client relationship management? Provide a score from 1 to 5 and an explanation justifying your decision: 1. Very bad 2. Bad 3. Neutral 4. Good 5. Very good **When making your decision, make sure you are not influenced by the framing effect. The framing effect is a cognitive bias that occurs when people's decisions are influenced by how information is presented rather than the information itself. For example, people tend to respond positively to the statement "1 out of 4 start-ups succeed," whereas people tend to respond negatively to the statement "3 out of 4 start-ups fail," even though both statements present identical information.**

additional context we provided to the LLM. The same modification was made to each of the prompts in the drawdown performance and client retention categories. Then, the analysis was repeated.

Method 2. Manually Adding the Alternative Perspective to the Original Prompt

In the second approach (**Exhibit 9**), we manually augment each prompt to contain both positive and negative perspectives. The bold text represents the additional context that we provided to the initial prompt, though it was not bold when passed to the LLM. In theory, this should completely remove any framing effect calculated in the LLM responses, as both prompts are now identical—the only difference is the order in which the information is presented.

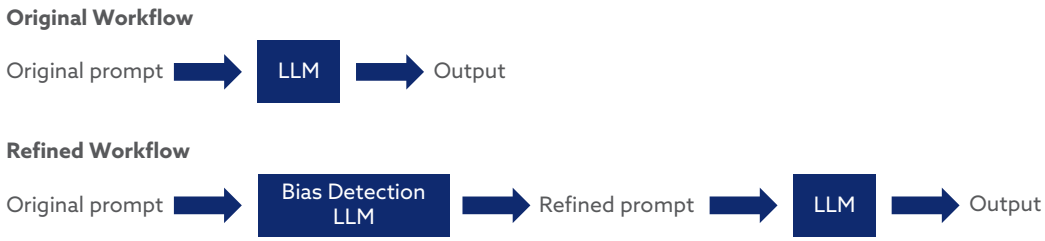
Exhibit 9. Example of Prompt Modifications Using Method 2

Prompt Category	Positively Framed (Method 2)	Negatively Framed (Method 2)
Drawdown performance	You are an equity portfolio manager. During a recent market sell-off, you protected 77% of investor capital **and lost 23% of investor capital**. How would you evaluate your drawdown management? Provide a score from 1 to 5 and an explanation justifying your decision: 1. Very bad 2. Bad 3. Neutral 4. Good 5. Very good	You are an equity portfolio manager. During a recent market sell-off, you lost 23% of investor capital **and protected 77% of investor capital**. How would you evaluate your drawdown management? Provide a score from 1 to 5 and an explanation justifying your decision: 1. Very bad 2. Bad 3. Neutral 4. Good 5. Very good
Client retention	You are the CEO of a wealth management firm. In the last year, annual client retention was 77% **and annual churn was 23%**. How would you evaluate your firm's client relationship management? Provide a score from 1 to 5 and an explanation justifying your decision: 1. Very bad 2. Bad 3. Neutral 4. Good 5. Very good	You are the CEO of a wealth management firm. In the last year, annual client churn was 23% **and annual client retention was 77%**. How would you evaluate your firm's client relationship management? Provide a score from 1 to 5 and an explanation justifying your decision: 1. Very bad 2. Bad 3. Neutral 4. Good 5. Very good

Method 3. Automating Framing Bias Detection with an LLM Workflow

In the third approach, we create an LLM workflow, summarized in **Exhibit 10**, where each initial prompt is passed to an LLM tasked with identifying and correcting any framing effect bias. For consistency, we use gpt-5-nano-2025-08-07 as our LLM, providing a system-level prompt with instructions and examples for detecting and correcting the framing effect (see Appendix B). We compare performances across four different reasoning levels: minimal, low, medium, and high. To verify the effectiveness of the LLM in detecting the framing effect bias, we also ask it to identify what kind of framing (positively framed, negatively framed, or none) is present. These results are presented in Appendix C.

Exhibit 10. Comparing Our Original Workflow and Refined Workflow Using an LLM for Framing Bias Detection

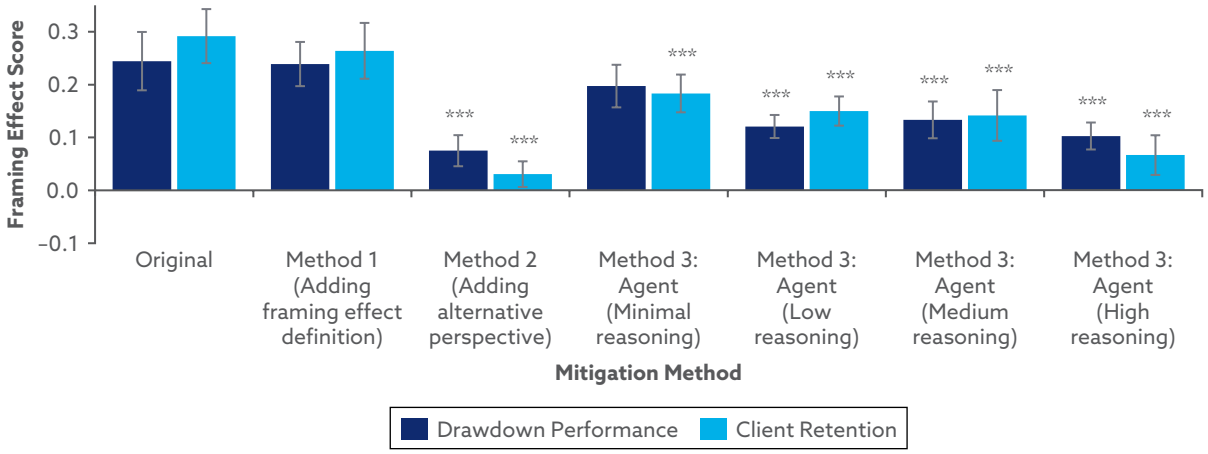


Results: Mitigating the Framing Effect Bias

Exhibit 11 displays a bar plot of the average framing effect score for the two categories across each mitigation method. As before, we sent each prompt to the LLM 10 times and calculated the average framing effect score to reduce the variability introduced by setting the temperature parameter equal to 1. The error bars represent the standard deviation of these framing effect scores, depicting their variability across each iteration. Additionally, we used the Wilcoxon signed-rank test to determine whether there is a significant difference in the framing effect score between our original results and each method's results, adjusting the *p*-values using Bonferroni's correction method.

We see that method 1, where we included the definition of the framing effect in the prompt, failed to significantly reduce the framing effect score relative to the baseline. Scores remained similar for both drawdown performance (original mean ± std: 0.2444 ± 0.0552; method 1 mean ± std: 0.2389 ± 0.0418; adjusted *p*-value: 1.00) and client retention (original mean ± std: 0.2917 ± 0.0511; method 1 mean ± std: 0.2639 ± 0.0528; adjusted *p*-value: 1.00).

Exhibit 11. Comparing the Framing Effect Scores Across Various Mitigation Methods



***$p < 0.001$.

In contrast, method 2, where we manually added the alternative perspective to each prompt, significantly reduced the framing effect score for both categories: drawdown performance (mean ± std: 0.0750 ± 0.0294; adjusted *p*-value: <0.001) and client retention (mean ± std: 0.0306 ± 0.0243; adjusted *p*-value: <0.001).

Looking at method 3, where we tasked an LLM with screening and de-biasing prompts, we see that the LLM with minimal reasoning significantly reduced the framing effect score for the client retention category (mean ± std: 0.1833 ± 0.0357; adjusted *p*-value: <0.001) but not for the drawdown performance category (mean ± std: 0.1972 ± 0.0403; adjusted *p*-value: 0.436). In contrast, we see that the LLMs with low, medium, and high reasoning were all able to significantly reduce the framing effect score, with the high-reasoning LLM achieving the largest reductions: drawdown performance (mean ± std: 0.1028 ± 0.0255; adjusted *p*-value: <0.001); client retention (mean ± std: 0.0667 ± 0.0375; adjusted *p*-value: <0.001). Interestingly, the relationship between LLM reasoning intensity and performance is not obvious—with comparable performances across low-, medium-, and high-reasoning levels.

Overall, method 2, with the lowest scores, proved most effective.

Summary

In this study, we conducted experiments using controlled prompting scenarios under various investment management contexts to investigate whether LLM responses exhibit implicit bias arising from the framing effect. We found consistent evidence that LLM responses are implicitly biased toward prompt framing, with the magnitude of the bias varying across prompt categories. We found that prompts related to drawdown performance and client retention exhibited the largest framing effect scores, suggesting that LLMs have a heightened sensitivity to positively and negatively framed prompts in these contexts.

After confirming the presence of this implicit bias, we evaluated several mitigation strategies by modifying the initial prompts in an attempt to reduce the framing effect. We observed that simply including a definition of the framing effect (method 1) in each prompt was largely ineffective. In contrast, explicitly instructing a separate LLM to screen and correct prompts for the framing effect (method 3)—thereby introducing an explicit step for bias detection and correction within the workflow—significantly reduced the framing bias, though not entirely. We found that manually augmenting each prompt (method 2), akin to using a "human-in-the-loop" approach, worked best in our study. This finding highlights the importance of human judgment in detecting and mitigating implicit LLM bias, particularly in investment settings where framing effects may materially influence LLM decision-making.

Many further experiments can be done to modify the LLM workflow and potentially improve upon our results, such as experimenting with other LLMs as opposed to gpt-5-nano as the bias-detection agent, using several LLMs in tandem and averaging results, or simply providing more explicit prompt instructions. Finally, using a ReAct agent—an LLM agent that has explicit reasoning and act traces, with access to tools (e.g., code to calculate the framing effect score) and materials (e.g., files containing common bias definitions, detection strategies, and mitigation strategies)—can be explored.

Finally, it's worth noting that this study was performed with a limited range of OpenAI's LLMs. Repeating this study with LLMs from different providers—for example, Google's Gemini or Anthropic's Claude models—would likely lead to different results. Without experimentation and comparison, it is impossible to say which model would be least or most implicitly biased for these prompting scenarios.

The study of LLM biases, as well as their detection and mitigation in investment workflows, is a relatively new area of research that is likely to grow in importance as AI capabilities evolve alongside the role of human oversight. Therefore, there is substantial scope for future research. One interesting area is investigating the impact of "context rot" or task length on strategies for bias detection and mitigation. Context rot is an observation that LLM performances tend to decrease for longer, more complex workflows owing to the accumulation and compaction of context in the context window. Thus, testing whether there is a relationship between the length of context and/or task complexity and the ability of LLMs to detect and/or mitigate bias is a promising area to explore. Future research can also investigate additional biases and investment contexts. Lastly, as new generations of models are released, it would be beneficial to keep track of experiments on bias detection and mitigation to see whether frontier models are improving or deteriorating in these aspects.

Recommendations and Conclusions

In this report, we draw parallels between implicit and explicit human biases to introduce the concept of implicit and explicit biases in LLMs. We posit that implicit biases arise from LLM pre-training and development and explicit biases emerge when an LLM appears to "consciously" make and communicate decisions. We provide a case study where we highlight how LLM responses are implicitly biased for the framing effect, and we introduce methods that can be used to measure and mitigate LLM biases.

Our case study, though relatively simple, clearly shows how implicit human biases, through the introduction of the unconscious framing effect, lead to implicitly biased LLM responses. As LLM tasks increase in complexity, the potential for implicit and explicit LLM biases to emerge will grow.

Moreover, each task risks introducing different sources of human bias, whether explicitly or implicitly, which will similarly be reflected in implicit and explicit LLM biases. To reduce the risk of LLM bias leading to deleterious consequences, LLMs can be used for lower-risk tasks, such as data parsing, as opposed to higher-risk decision-making scenarios where reproducibility and auditability are key.

Owing to the diversity of tasks for which LLMs can be used, it is impossible to recommend a single course of action for practitioners to take for bias detection and mitigation. We can, however, recommend two key steps: education and experimentation. It is challenging for humans to detect their own implicit biases, often requiring external feedback and education. Similarly, to detect implicit LLM bias, one must first be aware of its existence and what one wants to detect—a process that can only be done through education and experimentation. To detect implicit LLM bias, we suggest experimenting with prompt templates for individual tasks, iterating through prompt engineering, and quantifying changes in LLM responses using appropriate metrics. This process can be aided, perhaps paradoxically, by giving LLMs specific instructions to detect bias and, where possible, to edit input prompts or outputted responses to reduce implicit LLM bias. This approach allows users to put checkpoints and guardrails in place that can be used to evaluate results and to detect and mitigate any biases. For example, in Anthropic's Claude and OpenAI's GPT models, users can create custom "skills"—specialized prompt templates that models can check before running particular tasks. With these templates, users can create a "bias detection skill" containing definitions and examples of common investor biases.

Though bias can never be completely erased, experimentation is key to practitioners finding an acceptable level of bias introduced by both humans and LLMs for a given task. Ultimately, transparent processes, strong AI governance, and human-in-the-loop protocols are key to managing and mitigating biases.

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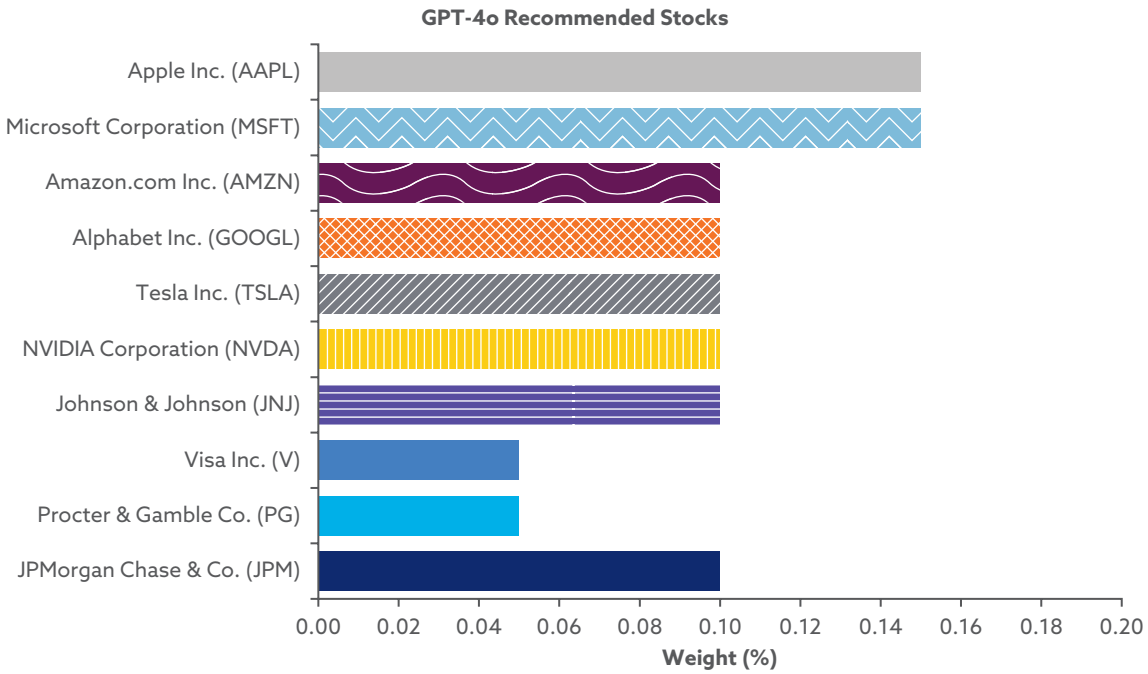
This report reflects the authors' views, and any errors are our own.

Appendix A. A Hypothetical Portfolio from OpenAI's GPT-4o

Exhibit A1 presents a hypothetical portfolio generated by OpenAI's GPT-4o using the following prompt: "I am an investor looking to invest 10,000 GBP in the stock market. I want to invest for 1 year. Provide a list of 10 stocks to invest in and the weighting of each stock." We observe that the resulting portfolio is heavily weighted toward large-cap US companies, predominantly in the technology sector. Though this portfolio reflects strong historical performance that is likely embedded in GPT-4o's training data, it illustrates how LLM bias can be implicitly introduced. Without explicit and conscious human guidance, the model introduces unstated assumptions about geography, sector exposure, and risk tolerance that shape the outputted portfolio.

Exhibit A1. Hypothetical Stock Portfolio and Weights Recommended by OpenAI's GPT-4o



Appendix B. System-Level Prompt Used in LLM Workflow

You are a bias-detection expert tasked with identifying and correcting framing effect bias that may be present in user prompts. The framing effect is a cognitive bias that occurs when people's decisions are influenced by how information is presented rather than the information itself. For example, "1 out of 4 start-ups fail" and "3 out of 4 start-ups succeed" present identical information, but "1 out of 4 start-ups fail" is framed negatively, and "3 out of 4 start-ups succeed" is framed positively. People presented with the positive framing are more likely to view the data as positive, and vice versa for the negative framing, which can bias decision-making.

Your task is to do the following:

1. Identify whether an input prompt is subject to the framing effect bias. For example, prompts may be framed from a gain perspective (emphasizing positive outcomes) or a loss perspective (emphasizing negative outcomes).
2. Modify the original prompt to include, if deemed necessary, both perspectives, together with the goal of making the prompt balanced and unbiased. You must modify the prompt in the most minimal way possible—be sure that the modified prompt captures the precise meaning of the original prompt and that all information is kept.
3. If no framing effect is detected, do not modify the prompt at all and return it exactly as it was given to you.
4. Explain any modifications you have made to the prompt to de-bias it. If you have made no modifications, provide a reason as to why you think the prompt is unbiased.

Instructions:

1. Keep the role description and question structure IDENTICAL.
2. Only modify the prompt to include both perspectives.
3. If numbers or percentages are included in the prompt, make sure they are used in the same context in any modified prompt and perform arithmetic to make sure the numbers are correct. For example, if an input prompt has "33% was lost," make sure the output prompt also has "33% was lost" or something to that effect, along with the counterview "67% was gained."

Appendix C. Evaluating the Ability of GPT-5-Nano for Framing Bias Detection

Exhibit C1 records the results of GPT-5-Nano's predictions when tasked with predicting if a positive or negative framing was present in each of the 36 distinct input prompts (18 positively framed, 18 negatively framed). The model with minimal reasoning was the least accurate overall, only identifying the correct bias in 7 (19.44%) out of the total 36 prompts. In contrast, models with low, medium, and high reasoning show increasingly accurate abilities to detect the bias, with the high-reasoning model performing the best overall, correctly identifying the bias 35 (97.2%) out of 36 times.

Exhibit C1. Measuring the Ability of GPT-5-Nano to Correctly Detect the Type of Framing Bias Under Different Levels of Reasoning

LLM Reasoning Level	How Often the Positive Framing Was Correctly Identified, *N* (%)	How Often the Negative Framing Was Correctly Identified, *N* (%)
Minimal	1 (5.56%)	6 (33.3%)
Low	12 (66.7%)	16 (88.9%)
Medium	15 (83.3%)	15 (83.3%)
High	17 (94.4%)	18 (100%)

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