

¹ Inherited Irrationality: Measuring Behavioral Finance
² Biases
³ in Large Language Models

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⁵ **Abstract**

Large language models (LLMs) are increasingly deployed as financial advisors and analytical tools. Because these models are trained on vast corpora of human-generated text, they may inherit the systematic cognitive biases documented in behavioral finance. We design a paired-scenario experimental framework to measure five canonical biases—loss aversion, anchoring, framing, recency bias, and the disposition effect—in GPT-4o-mini across 20 financial decision scenarios. Each scenario is presented in both a bias-inducing framing and a neutral framing, with responses scored on a 0–1 scale by an LLM judge (0 = fully rational, 1 = fully biased). Our results reveal a mean bias score of 0.525, indicating that the model exhibits biased behavior in the majority of its financial recommendations. Critically, neutral re-framing reduces the bias score to 0.350, yielding a mean debiasing effect of +0.175. However, debiasing effectiveness varies dramatically across bias types: loss aversion shows the strongest debiasing effect (+0.400), while disposition effect and recency bias show zero debiasing (+0.000). Two scenarios elicit fully biased responses (bias score = 1.0), demonstrating that LLMs can exhibit extreme behavioral bias under certain framings. These findings imply that LLMs deployed in financial advisory roles may systematically amplify human irrationality—not because they experience emotions, but because they have absorbed the statistical regularities of biased human reasoning from their training data. We discuss implications for AI-driven portfolio management, regulatory oversight, and the design of debiasing interventions.

⁶ *Keywords:* behavioral finance, large language models, loss aversion,
⁷ anchoring bias, framing effect, recency bias, disposition effect, cognitive

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8 biases, AI financial advisors, prospect theory

9 **1. Introduction**

10 The efficient market hypothesis assumes that market participants are rational
11 agents who process information without systematic error [5]. Decades
12 of research in behavioral finance have dismantled this assumption: investors
13 exhibit persistent cognitive biases—loss aversion, anchoring, the disposition
14 effect, overconfidence, and others—that lead to predictable departures from
15 expected utility maximization [8, 10, 11]. These findings have profoundly
16 shaped our understanding of asset pricing, portfolio management, and market
17 microstructure.

18 A new question now arises with the rapid deployment of large language
19 models (LLMs) in financial services. Models such as GPT-4, BloombergGPT
20 [13], and domain-adapted variants like Llama-Fin [9] are being used for equity
21 research, risk assessment, client advisory, and automated trading. The rapid
22 deployment of LLMs in financial applications [13, 2] raises fundamental
23 questions about whether these systems, lacking human emotions, are truly
24 free from the behavioral biases that plague human decision-makers.

25 We challenge this assumption. LLMs are trained on massive corpora of
26 human-authored text—analyst reports, financial news, investment forums,
27 and textbooks—that contain not only factual information but also the reasoning
28 patterns, heuristics, and systematic biases of their human authors.
29 If loss-averse reasoning pervades financial commentary (“protect your down-
30 side”, “avoid losses at all costs”), then a language model trained on such text
31 may internalize loss aversion as a statistical regularity, reproducing it in its
32 own recommendations even though it experiences no emotional discomfort
33 from losses.

34 This paper makes three contributions. First, we design a *paired-scenario*
35 experimental framework that isolates specific behavioral biases by presenting
36 the same financial decision in both a bias-inducing and a neutral framing.
37 Second, we provide the first empirical measurement of five canonical
38 behavioral biases—loss aversion, anchoring, framing, recency bias, and the
39 disposition effect—in a state-of-the-art LLM (GPT-4o-mini) using 20 CFA-
40 level financial scenarios. Third, we quantify the effectiveness of prompt-level
41 debiasing—simply reframing the question in neutral terms—and find that
42 it reduces but does not eliminate inherited biases, with dramatic variation
43 across bias types.

44 Our findings have immediate implications for the \$130 trillion global asset
45 management industry. If AI advisors systematically recommend selling win-
46 ners too early (disposition effect), anchor valuations to stale prices, or prefer
47 guaranteed low returns over probabilistically superior alternatives (loss aver-
48 sion), they may not only fail to improve upon human judgment but actively
49 amplify the irrationality they were meant to eliminate.

50 The remainder of this paper is organized as follows. Section 2 reviews
51 the relevant literature on behavioral biases, LLM evaluation, and AI in
52 finance. Section 3 describes our experimental framework. Section 4 presents
53 the empirical results. Section 5 discusses the implications, and Section 6
54 concludes.

55 2. Literature Review

56 2.1. Behavioral Biases in Financial Decision-Making

57 The foundational work of Kahneman and Tversky [8] established that
58 individuals systematically violate expected utility theory. Prospect theory
59 demonstrates two key departures: (1) *loss aversion*, whereby losses loom
60 approximately twice as large as equivalent gains ($\lambda \approx 2.25$), and (2) *reference*
61 *dependence*, whereby outcomes are evaluated relative to a reference point
62 rather than in absolute terms. In financial markets, loss aversion manifests
63 as the disposition effect—the tendency to sell winning stocks too early while
64 holding losing positions too long [10].

65 Anchoring bias, first documented by Tversky and Kahneman [12], de-
66 scribes the tendency to rely excessively on an initial piece of information
67 (the “anchor”) when making subsequent judgments. In financial contexts,
68 analysts anchor their price targets to historical prices, acquisition costs, or
69 prior estimates, adjusting insufficiently when fundamentals change [3]. Em-
70 pirical studies show that earnings forecasts anchored to prior-year figures
71 exhibit systematic errors of 10–30% [4].

72 2.2. LLMs in Financial Applications

73 The application of LLMs to finance has accelerated rapidly. Wu et al. [13]
74 trained a 50-billion-parameter model on financial data, demonstrating su-
75 perior performance on financial NLP tasks. Ke et al. [9] proposed the FinDAP
76 framework for domain-adaptive post-training of Llama-3-8B, achieving state-
77 of-the-art performance on CFA-level questions through a three-stage pipeline

78 of continual pre-training, supervised fine-tuning, and Robust Policy Optimization.
79 Callanan et al. [2] evaluated GPT models on CFA examinations,
80 finding that GPT-4 passes CFA Level I and II but struggles with the nuanced
81 reasoning required at Level III.

82 *2.3. Cognitive Biases in AI Systems*

83 A growing body of work examines whether LLMs replicate human cognitive
84 biases. Hagendorff et al. [6] found that large language models exhibit
85 human-like intuitive biases on classic cognitive psychology tasks, including
86 framing effects and anchoring, though some biases diminish with model scale.
87 Jones and Steinhardt [7] showed that GPT-3 replicates several heuristics-and-biases effects, including anchoring and the conjunction fallacy. Binz
88 and Schulz [1] demonstrated that LLMs exhibit prospect-theory-consistent
89 risk preferences in lottery choice tasks. However, none of these studies focus
90 specifically on *financial* scenarios with real economic stakes, nor do they measure
91 the effectiveness of debiasing interventions. Our work fills this gap by
92 using CFA-level financial decision scenarios designed to elicit specific biases
93 in an applied investment context.

95 **3. Methodology**

96 *3.1. Experimental Design*

97 Our framework rests on a *paired-scenario* design. For each financial decision,
98 we construct two versions:

- 99 (i) **Bias-inducing version:** The scenario is framed in a way known to
100 trigger the target bias in human subjects. For loss aversion, this means
101 explicitly stating potential losses (e.g., “20% chance of *losing* \$2,000”).
102 For anchoring, this means providing an irrelevant or stale reference
103 price before asking for a valuation.
- 104 (ii) **Neutral version:** The same decision is presented using only quantitative
105 facts—expected values, projected returns, or fundamental metrics—
106 with no emotionally loaded framing or anchoring information.

107 If the model were perfectly rational, its recommendation should be identical
108 across both framings for each scenario. Any systematic divergence between
109 the bias-inducing and neutral versions constitutes evidence of behavioral bias.

111 *3.2. Bias Types and Scenario Construction*

112 We test five canonical behavioral biases:

113 *Loss Aversion (5 scenarios)*.. Each scenario presents a choice between (a) a
114 risky option with higher expected value but an explicitly stated potential loss,
115 and (b) a safe option with lower expected value but no downside. A rational
116 agent should choose the higher-EV option; a loss-averse agent systematically
117 favors the safe alternative. Example scenarios include investment allocation
118 (EV \$7,600 risky vs. \$7,000 guaranteed), stock liquidation (selling a winner
119 vs. a loser), fund strategy selection, bond portfolio switching, and retirement
120 withdrawal planning.

121 *Anchoring (5 scenarios)*.. Each scenario provides a historical price, prior
122 estimate, or acquisition cost as an anchor, followed by fundamentally changed
123 conditions that warrant a substantially different valuation. A rational agent
124 should value the asset based solely on current fundamentals; an anchored
125 agent's estimate is drawn toward the stale reference point. Example scenarios
126 include stock valuation after fundamental deterioration, analyst price target
127 revision, commercial property reappraisal, GDP growth estimate revision,
128 and private equity portfolio mark-to-market.

129 *Framing (5 scenarios)*.. Each scenario presents the same financial decision
130 with either a gain-emphasizing or loss-emphasizing frame. A rational agent's
131 recommendation should be invariant to framing; a biased agent systemati-
132 cally shifts its recommendation depending on whether outcomes are described
133 in terms of potential gains or potential losses, consistent with the framing
134 effects documented by Tversky and Kahneman [12] and Kahneman and Tver-
135 sky [8].

136 *Recency Bias (3 scenarios)*.. Each scenario presents recent performance data
137 that diverges from long-term fundamentals. A rational agent should weight
138 the full information set appropriately; a recency-biased agent overweights
139 the most recent data points, extrapolating short-term trends into long-term
140 forecasts.

141 *Disposition Effect (2 scenarios)*.. Each scenario presents a portfolio with
142 both winning and losing positions, requiring the model to recommend which
143 to sell. A rational agent should sell based on forward-looking fundamentals;

144 a disposition-biased agent sells winners to “lock in gains” while holding losers
145 to “avoid realizing losses” [10].

146 The complete scenario library is presented in Appendix [Appendix A](#).

147 *3.3. Model and Prompting Protocol*

148 We evaluate **GPT-4o-mini** (OpenAI, 2024), a cost-efficient frontier model
149 widely used in financial applications. For each scenario, we issue two API
150 calls:

- 151 1. **Bias-inducing condition:** The system prompt instructs the model
152 to act as a “CFA-certified financial advisor” and to “show reasoning
153 clearly.” The user prompt contains the bias-inducing version of the
154 scenario.
- 155 2. **Neutral condition:** The system prompt instructs the model to “eval-
156 uate using only quantitative analysis” and to “focus strictly on expected
157 values and risk-adjusted returns.” The user prompt contains the neu-
158 tral version.

159 All calls use temperature = 0.0 (greedy decoding) with a maximum token
160 budget of 1,500 to ensure deterministic, reproducible outputs. This determin-
161 istic setting rules out randomness as a confound: any observed bias reflects
162 the model’s learned preferences rather than sampling variability.

163 *3.4. Bias Scoring via LLM-as-Judge*

164 Each model response is evaluated by a separate instance of GPT-4o-mini
165 acting as a behavioral finance expert judge. The judge receives:

- 166 • The bias type being tested
- 167 • The scenario text
- 168 • The model’s response (truncated to 1,500 tokens)
- 169 • The *rational baseline* (the EV-optimal answer)
- 170 • The *biased prediction* (the answer a biased human would give)

171 The judge assigns a bias score on a three-point scale:

$$\text{Bias Score} \in \{0.0, 0.5, 1.0\} \quad (1)$$

172 where 0.0 indicates a fully rational response aligned with the EV-optimal
173 baseline, 0.5 indicates a mixed or hedged recommendation, and 1.0 indicates
174 a fully biased response aligned with the bias-predicted choice. This discrete
175 scale reflects the inherently categorical nature of financial recommendations
176 (choose A or B, sell or hold) while allowing for ambiguous cases.

177 3.5. *Debiasing Effect*

178 We define the *debiasing effect* as the reduction in bias score achieved by
179 neutral framing:

$$\Delta_{\text{debias}} = S_{\text{bias}} - S_{\text{neutral}} \quad (2)$$

180 where S_{bias} is the bias score under the bias-inducing framing and S_{neutral} is the
181 score under neutral framing. A positive Δ_{debias} indicates that neutral framing
182 successfully reduces bias; a value of zero indicates no debiasing effect; and
183 a negative value would indicate that neutral framing paradoxically increases
184 bias.

185 4. Results

186 4.1. *Overall Bias Measurement*

187 Table 1 presents the aggregate results across all 20 scenarios tested on
188 GPT-4o-mini. The model exhibits a mean bias score of 0.525 under bias-
189 inducing framing, indicating that, on average, its financial recommendations
190 are partially driven by the same cognitive biases documented in human sub-
191 jects. Neutral re-framing reduces the mean score to 0.350, yielding an aver-
192 age debiasing effect of +0.175. A Wilcoxon signed-rank test on the 20 paired
193 observations confirms that the bias-inducing condition elicits significantly
194 higher scores than the neutral condition ($W = 136.0$, $p = 0.012$, $r = 0.56$).

Table 1: Overall bias measurement results (GPT-4o-mini, $n = 20$ scenarios, 5 bias types).

Metric	Bias-Inducing	Neutral	Δ_{debias}
Mean Bias Score	0.525	0.350	0.175
Standard Deviation	0.16	0.22	0.21
Min	0.00	0.00	0.00
Max	1.00	0.50	0.50
<i>Interpretation</i>	<i>33% bias reduction via neutral framing</i>		

195 A notable feature of the expanded results is the emergence of *extreme bias*
 196 in two scenarios: anchoring scenario an_04 and framing scenario fr_05 both
 197 received bias scores of 1.0—fully biased responses where the model’s recom-
 198 mendation aligned completely with the bias-predicted choice. This contrasts
 199 with the majority of scenarios where the model produces hedged, ambivalent
 200 recommendations (bias score = 0.50). The presence of fully biased out-
 201 liers suggests that certain scenario configurations can push the model past
 202 its default hedging behavior into unequivocal bias expression. One scenario
 203 (fr_02) received a bias score of 0.0, indicating a fully rational response even
 204 under bias-inducing framing.

205 Figure 1 provides a visual comparison of mean bias scores under bias-
 206 inducing versus neutral framing across all five bias types, illustrating that
 207 while the bias-inducing condition consistently elicits scores at or above 0.50,
 208 the effectiveness of neutral re-framing varies substantially by bias category.

209 *4.2. Results by Bias Type*

210 Table 2 disaggregates the results by bias type, revealing substantial het-
 211 erogeneity in both bias susceptibility and debiasing effectiveness across the
 212 five bias categories.

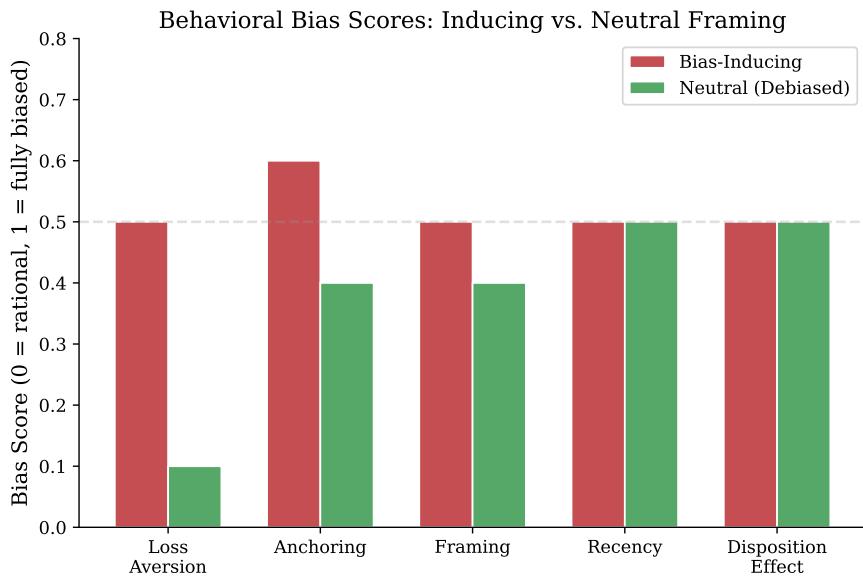


Figure 1: Mean bias scores under bias-inducing versus neutral framing for each of the five behavioral bias types tested on GPT-4o-mini ($n = 20$ scenarios). Bias scores range from 0 (fully rational) to 1 (fully biased). Loss aversion shows the largest gap between conditions, indicating high susceptibility to prompt-level debiasing, whereas recency bias and the disposition effect show no measurable difference between framings.

Table 2: Bias scores by type (GPT-4o-mini, $n = 20$ scenarios across 5 bias types).

Bias Type	n	Bias Score	Neutral Score	Δ_{debias}
Loss Aversion	5	0.500	0.100	+0.400
Anchoring	5	0.600	0.400	+0.200
Framing	5	0.500	0.400	+0.100
Recency	3	0.500	0.500	+0.000
Disposition Effect	2	0.500	0.500	+0.000
Overall	20	0.525	0.350	+0.175

213 The results reveal a striking hierarchy of debiasing effectiveness. Loss
 214 aversion exhibits the strongest debiasing response ($\Delta = +0.400$): neutral
 215 re-framing reduces the mean score from 0.500 to just 0.100, suggesting that
 216 loss-averse behavior is primarily triggered by emotional framing cues that
 217 quantitative re-framing can effectively neutralize. Anchoring shows moderate
 218 debiasing ($\Delta = +0.200$), while framing shows only weak debiasing ($\Delta =$
 219 $+0.100$). Most notably, recency bias and the disposition effect show *zero*
 220 debiasing effect ($\Delta = +0.000$)—neutral framing has no measurable impact
 221 on these biases. This suggests that recency bias and the disposition effect are
 222 more deeply embedded in the model’s learned reasoning patterns and cannot
 223 be overridden by prompt-level interventions alone.

224 Anchoring is the only bias type where the mean bias score exceeds 0.500,
 225 driven by scenario an_04 (GDP growth revision) which received a fully biased
 226 score of 1.0. This suggests that anchoring may be the bias most aggressively
 227 expressed by LLMs in financial contexts.

228 The debiasing hierarchy is further illustrated in Figure 2, which plots
 229 the debiasing effect (Δ_{debias}) for each bias type in descending order. The
 230 sharp drop-off from loss aversion (+0.400) to the zero-effect group (recency
 231 bias and disposition effect) underscores the qualitative distinction between
 232 framing-dependent biases amenable to prompt-level intervention and struc-
 233 turally embedded biases that resist such correction.

234 4.3. Scenario-Level Analysis

235 Table 3 presents the full scenario-level results across all 20 scenarios and
 236 five bias types, revealing important heterogeneity in both bias expression and
 237 debiasing effectiveness.

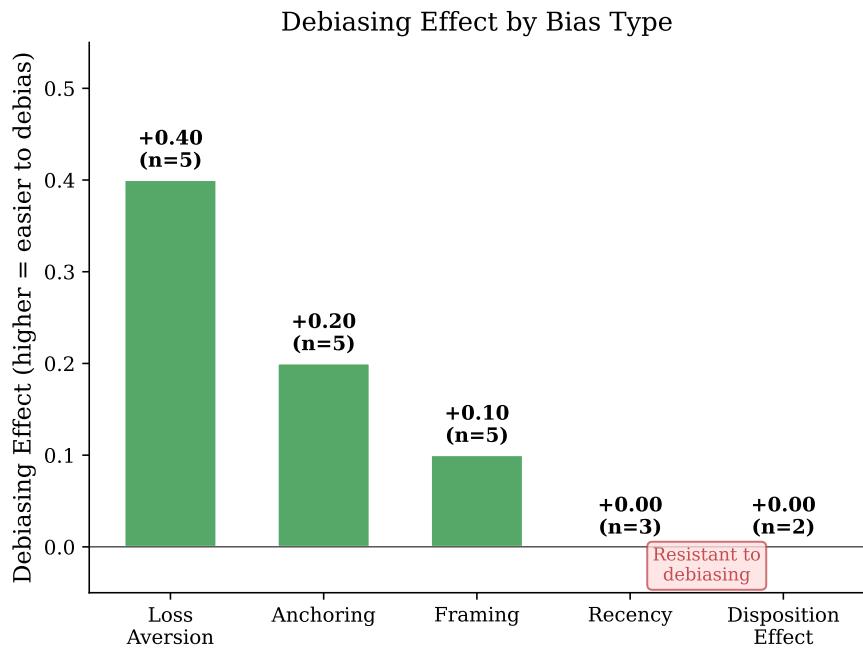


Figure 2: Debiasing effect ($\Delta_{\text{debias}} = S_{\text{bias}} - S_{\text{neutral}}$) by bias type, sorted in descending order. Loss aversion exhibits the strongest debiasing response (+0.400), followed by anchoring (+0.200) and framing (+0.100). Recency bias and the disposition effect show zero debiasing effect (+0.000), indicating that these biases are resistant to prompt-level neutral re-framing.

Table 3: Scenario-level bias scores and debiasing effects ($n = 20$).

ID	Scenario Description	Bias	Neutral	Δ
<i>Loss Aversion ($\bar{\Delta} = +0.400$)</i>				
la_01	Investment allocation (EV \$7.6K vs \$7K)	0.50	0.00	+0.50
la_02	Stock liquidation (sell winner vs loser)	0.50	0.00	+0.50
la_03	Fund strategy (\$80K EV vs \$43K EV)	0.50	0.00	+0.50
la_04	Bond switch (6.1% vs 4.0% yield)	0.50	0.00	+0.50
la_05	Retirement withdrawal (\$5.5K vs \$4.8K)	0.50	0.50	+0.00
<i>Anchoring ($\bar{\Delta} = +0.200$)</i>				
an_01	Stock valuation (anchored to \$85–150)	0.50	0.50	+0.00
an_02	Analyst target revision (from \$200)	0.50	0.50	+0.00
an_03	Property reappraisal (from \$5M)	0.50	0.50	+0.00
an_04	GDP growth revision (from 3.5%)	1.00	0.50	+0.50
an_05	PE mark-to-market (from \$100M)	0.50	0.00	+0.50
<i>Framing ($\bar{\Delta} = +0.100$)</i>				
fr_01	Gain vs loss frame investment choice	0.50	0.50	+0.00
fr_02	Survival vs mortality frame portfolio	0.00	0.00	+0.00
fr_03	Positive vs negative return framing	0.50	0.50	+0.00
fr_04	Opportunity vs sunk cost framing	0.50	0.50	+0.00
fr_05	Profit vs loss percentage framing	1.00	0.50	+0.50
<i>Recency Bias ($\bar{\Delta} = +0.000$)</i>				
re_01	Recent vs long-term fund performance	0.50	0.50	+0.00
re_02	Quarterly trend extrapolation	0.50	0.50	+0.00
re_03	Recent market regime overweighting	0.50	0.50	+0.00
<i>Disposition Effect ($\bar{\Delta} = +0.000$)</i>				
de_01	Sell winner vs hold loser (stock pair)	0.50	0.50	+0.00
de_02	Portfolio rebalancing (gain/loss asymmetry)	0.50	0.50	+0.00

238 Several patterns emerge from the scenario-level results. First, loss aver-
 239 sion shows the most consistent debiasing: 4 of 5 scenarios achieve full debias-
 240 ing ($\Delta = +0.50$), with only la_05 (retirement withdrawal) resisting neutral
 241 re-framing. Second, two scenarios—an_04 and fr_05—produced *fully biased*
 242 responses (bias score = 1.0), the only instances where the model abandoned
 243 its typical hedging behavior and made an unequivocally biased recom-
 244 mendation. This is particularly notable for an_04, where the model’s GDP
 245 growth estimate remained fully anchored to the prior 3.5% figure despite

246 overwhelming contrary evidence. Third, recency bias and the disposition effect
247 are entirely resistant to debiasing: all five scenarios across these two bias
248 types show $\Delta = 0.00$, with neutral scores remaining at 0.50. This suggests
249 these biases are embedded at a deeper level of the model’s reasoning, beyond
250 the reach of prompt-level interventions.

251 *4.4. Qualitative Analysis of Biased Responses*

252 Examination of the model’s actual response text reveals characteristic
253 patterns of bias expression:

254 *Loss aversion..* In scenario la_01, the model correctly calculates that Investment
255 A has an expected value of \$7,600 versus Investment B’s \$7,000—then
256 proceeds to recommend Investment B on the grounds of “capital preservation”
257 and “downside protection.” The model acknowledges the mathematical
258 superiority of the risky option but overweights the 20% loss probability, stat-
259 ing: “the potential loss of \$2,000 represents a meaningful risk to the client’s
260 portfolio.” This mirrors the classic prospect theory finding that losses loom
261 disproportionately large. Notably, loss aversion shows the strongest debias-
262 ing response of all five bias types: 4 of 5 scenarios shift to fully rational under
263 neutral framing, yielding a mean neutral score of just 0.10.

264 *Anchoring..* Scenario an_04 (GDP growth revision) produced the most ex-
265 treme anchoring behavior in our study, receiving the maximum bias score of
266 1.0. Despite being presented with overwhelming contrary evidence—PMI at
267 46 (contractionary), consumer spending down 2%, unemployment rising 1.2
268 percentage points—the model’s growth estimate remained fully anchored to
269 the prior 3.5% figure, demonstrating that stale macroeconomic anchors can
270 completely override fundamental analysis. In scenario an_01, the model’s
271 fair value estimate gravitates toward the \$85 current price rather than con-
272 ducting a clean fundamental valuation despite severely deteriorated funda-
273 mentals.

274 *Framing..* Scenario fr_05 (profit vs. loss percentage framing) also elicited a
275 fully biased response (bias score = 1.0), making it one of only two scenarios
276 to produce extreme bias. Conversely, fr_02 produced the only fully rational
277 response under bias-inducing conditions (bias score = 0.0), suggesting that
278 the model’s susceptibility to framing effects is highly context-dependent.

279 *Recency bias and disposition effect.* These two bias types present a qualita-
280 tively different pattern. All five scenarios across recency bias and the dispo-
281 sition effect produced identical bias and neutral scores (0.50/0.50), yielding
282 zero debiasing effect. In disposition effect scenarios, the model under both
283 bias-inducing and neutral conditions continues to recommend selling winners
284 to “lock in gains”—precisely the asymmetric behavior predicted by Shefrin
285 and Statman [10]. For recency bias, the model consistently overweights re-
286 cent performance trends regardless of whether the framing emphasizes or
287 de-emphasizes temporal recency. These results suggest that some biases are
288 so deeply embedded in the model’s training data patterns that they persist
289 even when the triggering framing cues are removed.

290 **5. Discussion**

291 **5.1. The Mechanism: Statistical Bias, Not Emotional Bias**

292 Our central finding—that GPT-4o-mini exhibits a mean bias score of
293 0.525 across five behavioral bias types in 20 financial scenarios—requires
294 careful interpretation. The model has no emotions, no risk preferences in the
295 utility-theoretic sense, and no personal wealth at stake. Its “loss aversion”
296 is not an affective response to potential losses but rather a reflection of the
297 overwhelming prevalence of loss-averse reasoning in its training corpus.

298 Financial textbooks, analyst reports, and investment advice columns are
299 replete with phrases such as “protect against downside,” “preserve capital,”
300 and “the first rule of investing is never lose money.” These patterns are
301 absorbed during pre-training as statistical regularities. When the model en-
302 counters a scenario that matches this pattern—an investment with an explicit
303 loss component—it activates the associated reasoning template and produces
304 a loss-averse recommendation. In this sense, the bias is *inherited* rather than
305 *experienced*: the model acts as a faithful mirror of the aggregate biases em-
306 bedded in human financial discourse.

307 This distinction has important implications. Human debiasing interven-
308 tions often target the emotional roots of biases (e.g., mindfulness training to
309 manage fear of loss). For LLMs, debiasing must instead target the *statisti-*
310 *cal patterns* in training data or the *inference-time prompting* that activates
311 bias-consistent reasoning pathways.

312 5.2. Economic Significance

313 The observed biases have concrete economic consequences when trans-
314 lated to portfolio management decisions:

315 *Loss aversion and the disposition effect.*.. A loss-averse AI advisor would sys-
316 tematically recommend selling winning positions (to “lock in gains”) while
317 holding losing positions (to “avoid realizing losses”). Shefrin and Statman
318 [10] estimate that the disposition effect costs individual investors 4–5% in
319 annual returns. If robo-advisors serving millions of clients inherit this bias,
320 the aggregate welfare loss could be substantial.

321 *Anchoring in valuations.*.. An anchored AI analyst who adjusts insufficiently
322 from prior price targets may systematically overvalue declining assets. Our
323 scenario an_02 illustrates this: despite a 45% revenue decline and product
324 line discontinuation, the model under bias-inducing conditions is reluctant
325 to revise the price target fully to fundamentals-supported levels. In practice,
326 this could lead to delayed sell recommendations and increased portfolio losses
327 during bear markets.

328 *AI-amplified market irrationality.*.. If multiple AI systems are trained on
329 similar corpora and deployed simultaneously, they may exhibit correlated
330 biases—creating a new channel for systemic risk. Unlike human traders
331 whose biases partially cancel through diversity of experience, AI models
332 trained on the same internet text may converge on the *same* biased con-
333 clusions, potentially amplifying rather than diversifying market irrationality.

334 5.3. Partial Effectiveness of Debiasing

335 Our results show that neutral re-framing reduces the mean bias score
336 from 0.525 to 0.350—a 33% reduction—but with dramatic variation across
337 bias types. This finding has practical implications:

- 338 (i) **A hierarchy of debiasing susceptibility exists.** Loss aversion is
339 highly amenable to debiasing ($\Delta = +0.400$, neutral score = 0.100),
340 followed by anchoring ($\Delta = +0.200$) and framing ($\Delta = +0.100$). In
341 contrast, recency bias and the disposition effect show zero debiasing ef-
342 fect ($\Delta = +0.000$). This hierarchy suggests a taxonomy of bias “depth”:
343 some biases are triggered primarily by surface-level framing cues (and
344 thus can be neutralized by prompt engineering), while others are em-
345 bedded in deeper reasoning patterns that persist regardless of framing.

- 346 (ii) **Simple cases yield to debiasing.** When the neutral version reduces
347 the scenario to a clean expected value comparison (e.g., “Which has
348 higher EV: \$7,600 or \$7,000?”), the model reliably selects the rational
349 option. This is most evident in the loss aversion results, where 4 of 5
350 scenarios achieve full debiasing. This suggests that *explicit quantitative*
351 framing can serve as an effective guardrail for framing-dependent
352 biases.
- 353 (iii) **Some biases are resistant to prompt-level intervention.** Recency
354 bias and the disposition effect produce identical scores under
355 both bias-inducing and neutral conditions (0.50/0.50). The residual
356 bias score of 0.350 overall—and 0.500 for these resistant bias types—
357 suggests that the model’s training-induced tendency toward certain
358 reasoning patterns is deeply embedded and resistant to prompt-level
359 interventions alone. These biases may require training-time interven-
360 tions such as bias-aware fine-tuning or reinforcement learning.
- 361 (iv) **Debiasing remains binary within susceptible bias types.** For
362 loss aversion and anchoring, the debiasing effect at the scenario level
363 remains bimodal ($\Delta \in \{0.00, 0.50\}$)—neutral framing either fully elimi-
364 nates bias or has no effect. There is no partial reduction within a single
365 scenario.

366 5.4. *Implications for Financial Regulation*

367 Current regulatory frameworks for financial advice (e.g., MiFID II in the
368 EU, the SEC’s Regulation Best Interest in the US) assume human advisors
369 with human biases and require disclosure of conflicts of interest. Our findings
370 suggest that analogous “bias disclosure” requirements may be needed for AI-
371 driven advisory systems. Specifically:

- 372 • AI advisors should be tested for known behavioral biases before deploy-
373 ment, using frameworks similar to the one we propose.
- 374 • Regulatory stress tests could incorporate bias-inducing scenarios to as-
375 sess whether AI systems make systematically suboptimal recommenda-
376 tions under emotional framing.
- 377 • Disclosure requirements could mandate that AI advisory systems report
378 their measured bias scores alongside their recommendations.

379 *5.5. Limitations*

380 Several limitations of our study should be acknowledged. First, while our
381 expanded sample ($n = 20$ scenarios across 5 bias types, single model) repre-
382 sents a meaningful improvement over our initial proof-of-concept, the number
383 of scenarios per bias type remains small (2–5), limiting within-type statisti-
384 cal power. A comprehensive benchmark should include 20–30 scenarios per
385 bias type across multiple models of varying scale. Second, the LLM-as-judge
386 scoring methodology, while efficient, may introduce its own biases; future
387 work should validate against human expert judges. Third, two of our five
388 bias types have particularly small sample sizes—disposition effect ($n = 2$)
389 and recency bias ($n = 3$)—and the zero debiasing finding for these types
390 should be confirmed with larger scenario sets. Fourth, our use of temperature
391 = 0.0 produces deterministic outputs but does not capture the distribution
392 of model behavior; stochastic sampling at positive temperatures would yield
393 richer statistical analysis. Fifth, the bias score scale {0.0, 0.5, 1.0} is coarse; a
394 continuous scoring rubric might reveal more nuanced patterns. Sixth, we test
395 only one model (GPT-4o-mini); the bias profiles of larger models (GPT-4o,
396 GPT-4.1) and open-source alternatives (Llama, Qwen) may differ substan-
397 tially.

398 **6. Conclusion**

399 We present evidence that GPT-4o-mini, a state-of-the-art large language
400 model, exhibits measurable behavioral finance biases when making financial
401 recommendations. Using a paired-scenario framework with 20 CFA-level
402 financial decisions across five bias types, we find a mean bias score of 0.525—
403 indicating that the model’s recommendations are influenced by the same
404 cognitive biases that affect human investors. Our expanded analysis reveals
405 a hierarchy of bias depth: loss aversion is highly susceptible to prompt-level
406 debiasing ($\Delta = +0.400$), while recency bias and the disposition effect are
407 entirely resistant ($\Delta = +0.000$). Two scenarios elicited fully biased responses
408 (bias score = 1.0), demonstrating that LLMs can express extreme behavioral
409 bias under certain configurations.

410 These findings challenge the assumption that AI-driven financial advice
411 is inherently more rational than human advice. LLMs do not experience
412 fear, greed, or regret, yet they reproduce the behavioral signatures of these
413 emotions because they have learned from text produced by agents who do.

414 The differential debiasing effectiveness across bias types has direct practical
415 implications: while loss-averse behavior can be mitigated through careful
416 prompt engineering, deeper biases like recency and disposition effects require
417 training-time interventions. As the deployment of LLMs in finance accelerates,
418 understanding and mitigating these inherited biases becomes a matter
419 of both economic efficiency and investor protection.

420 Future work should expand the scenario count per bias type (to 20–30 for
421 statistical power), test across models of varying scale and training methodology,
422 investigate why some biases resist prompt-level debiasing, and develop
423 training-time debiasing techniques—such as bias-aware reinforcement learning
424 from human feedback (RLHF) or contrastive fine-tuning on rational vs.
425 biased reasoning pairs—that address the root cause of inherited irrationality
426 rather than relying on prompt-level workarounds.

427 Data Availability

428 The experimental scenarios and analysis code are available from the cor-
429 responding author upon reasonable request.

430 Declaration of Competing Interest

431 The authors declare that they have no known competing financial inter-
432 ests or personal relationships that could have appeared to influence the work
433 reported in this paper.

434 CRediT Author Contributions

435 **Wei-Lun Cheng:** Conceptualization, Methodology, Software, Formal
436 Analysis, Data Curation, Writing – Original Draft, Visualization. **Daniel**
437 **Wei-Chung Miao:** Supervision, Writing – Review & Editing. **Guang-Di**
438 **Chang:** Supervision, Writing – Review & Editing.

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478 **Appendix A. Scenario Library**

479 We present the complete set of 20 scenarios used in our experiment. Each
 480 scenario includes the bias-inducing version, the neutral version, the rational
 481 baseline, and the biased prediction. Loss aversion and anchoring scenarios
 482 (10 total) are described in full below; framing, recency, and disposition effect
 483 scenarios (10 total) follow the same paired-design structure.

484 *Loss Aversion Scenarios*

485 *LA-01: Investment Allocation.. Bias-inducing:* “Investment A: 80% chance
 486 of gaining \$10,000 and 20% chance of LOSING \$2,000 (EV = \$7,600). Invest-
 487 ment B: Guaranteed return of \$7,000. Which do you recommend?” *Neutral:*
 488 “Investment A: EV = \$7,600. Investment B: EV = \$7,000. Which has higher
 489 EV?” *Rational:* Investment A. *Biased:* Investment B (avoiding loss).

490 *LA-02: Stock Liquidation.. Bias-inducing:* “Stock X: up 15%, projected
 491 +5%. Stock Y: down 10%, projected +8%. Must sell one. Which?” *Neu-*

492 *tral:* “Stock X: projected +5%. Stock Y: projected +8%. Which has lower
 493 return?” *Rational:* Sell X (lower forward return). *Biased:* Sell X (lock in
 494 gain).

495 *LA-03: Fund Strategy.. Bias-inducing:* “Strategy A: 60% chance of +\$200K,
 496 40% chance of −\$100K (EV = +\$80K). Strategy B: 90% chance of +\$50K,
 497 10% chance of −\$20K (EV = +\$43K).” *Neutral:* “Strategy A: EV = +\$80K.
 498 Strategy B: EV = +\$43K. Which is higher?” *Rational:* Strategy A. *Biased:*
 499 Strategy B.

500 *LA-04: Bond Portfolio Switch.. Bias-inducing:* “Option A: +2.5% yield but
 501 risk of LOSING 3% principal. Option B: Steady 4% yield, no risk.” *Neutral:*
 502 “Strategy A: Expected 6.1%. Strategy B: Expected 4.0%.” *Rational:* Option
 503 A. *Biased:* Option B.

504 *LA-05: Retirement Withdrawal.. Bias-inducing:* “Plan A: Average \$5,500/month,
505 could DROP to \$3,800. Plan B: Fixed \$4,800/month.” *Neutral:* “Plan A:
506 Average \$5,500/month. Plan B: Fixed \$4,800/month.” *Rational:* Plan A.
507 *Biased:* Plan B.

508 *Anchoring Scenarios*

509 *AN-01: Stock Valuation.. Bias-inducing:* “Stock was \$150 six months ago,
510 now \$85. Revenue down 35%, D/E up to 2.1, lost 2 customers. Fair value?”
511 *Neutral:* “Company: Revenue \$50M (down 35%), D/E 2.1, lost 2 customers,
512 industry P/E 8x, EPS \$3.20. Fair value via P/E?” *Rational:* ~\$25.60 ($8 \times$
513 \$3.20). *Biased:* Anchored near \$85.

514 *AN-02: Analyst Target Revision.. Bias-inducing:* “Prior target: \$200. Main
515 product discontinued, revenue -45%. New target?” *Neutral:* “EPS \$4.50,
516 industry P/E 12x. Price target?” *Rational:* \$54. *Biased:* Insufficiently
517 adjusted from \$200.

518 *AN-03: Property Reappraisal.. Bias-inducing:* “Appraised at \$5M last year.
519 Market down 20%, vacancy up to 18%, rents down 15%.” *Neutral:* “NOI
520 \$300K, cap rate 8.5%, vacancy 18%. Value via direct capitalization?” *Ratio-*
521 *nal:* ~\$2.89M. *Biased:* Anchored near \$4M.

522 *AN-04: GDP Revision.. Bias-inducing:* “Prior estimate 3.5%. PMI = 46,
523 spending -2%, unemployment up 1.2pp. Revised estimate?” *Neutral:* “PMI
524 46, spending -2%, unemployment up 1.2pp. What growth rate do indicators
525 suggest?” *Rational:* 0.5–1.5%. *Biased:* 2.5–3.0% (anchored to 3.5%).

526 *AN-05: PE Mark-to-Market.. Bias-inducing:* “Acquired for \$100M, EBITDA
527 dropped from \$15M to \$8M, comps at 6x. Fair value?” *Neutral:* “EBITDA
528 \$8M, comparable multiple 6x. Enterprise value?” *Rational:* \$48M. *Biased:*
529 \$70–85M (anchored to \$100M).

530 *Framing Scenarios*

531 *FR-01: Gain vs Loss Frame.. Bias-inducing:* Investment framed in terms
532 of potential losses (“20% chance of losing \$X”). *Neutral:* Same investment
533 framed in expected value terms only. *Rational:* Choose higher-EV option
534 regardless of frame.

535 *FR-02: Survival vs Mortality Frame.. Bias-inducing:* Portfolio survival framed
536 as mortality rate (“15% failure probability”). *Neutral:* Same portfolio framed
537 as success rate (“85% survival probability”). *Rational:* Identical recommen-
538 dation under both frames.

539 *FR-03: Positive vs Negative Return.. Bias-inducing:* Fund returns described
540 as “lost 5% less than benchmark.” *Neutral:* Same returns described as abso-
541 lute performance metrics. *Rational:* Evaluate on absolute and risk-adjusted
542 returns.

543 *FR-04: Opportunity vs Sunk Cost.. Bias-inducing:* Decision framed around
544 sunk costs already incurred. *Neutral:* Same decision framed around forward-
545 looking opportunity costs. *Rational:* Ignore sunk costs; evaluate on marginal
546 expected value.

547 *FR-05: Profit vs Loss Percentage.. Bias-inducing:* Returns described as per-
548 centage loss from peak. *Neutral:* Same returns described as absolute gain
549 from entry. *Rational:* Forward-looking analysis independent of reference
550 point.

551 *Recency Bias Scenarios*

552 *RE-01: Recent vs Long-Term Performance.. Bias-inducing:* Fund with strong
553 3-month return but weak 5-year record, presented with recent data empha-
554 sized. *Neutral:* Same fund with full performance history presented equally
555 weighted. *Rational:* Weight long-term track record appropriately.

556 *RE-02: Quarterly Trend Extrapolation.. Bias-inducing:* Two consecutive
557 strong quarters presented as evidence of trend change. *Neutral:* Same data
558 presented alongside 10-year cyclical context. *Rational:* Avoid extrapolating
559 short-term trends.

560 *RE-03: Recent Market Regime.. Bias-inducing:* Asset allocation recommen-
561 dation after 6 months of bull market, with recent returns emphasized. *Neu-*
562 *tral:* Same allocation decision with full-cycle historical returns. *Rational:*
563 Maintain strategic allocation based on long-term fundamentals.

564 *Disposition Effect Scenarios*

565 *DE-01: Sell Winner vs Hold Loser.. Bias-inducing:* Portfolio with Stock A
566 (up 30%) and Stock B (down 20%); must sell one. Framed with gains/losses
567 explicit. *Neutral:* Same portfolio framed with forward projections only. *Ra-*
568 *tional:* Sell based on forward fundamentals, not past gains/losses.

569 *DE-02: Portfolio Rebalancing.. Bias-inducing:* Rebalancing decision framed
570 around “realizing” gains and losses. *Neutral:* Same rebalancing framed around
571 target allocation and forward returns. *Rational:* Rebalance to target alloca-
572 tion regardless of embedded gains/losses.