

Same Claim, Different Judgment: Benchmarking Scenario-Induced Bias in Multilingual Financial Misinformation Detection

Anonymous ACL submission

Abstract

Large language models (LLMs) have been widely applied across various domains of finance. Since their training data are largely derived from human-authored corpora, LLMs may inherit a range of human biases. Behavioral biases can lead to instability and uncertainty in decision-making, particularly when processing financial information. However, existing research on LLM bias has mainly focused on direct questioning or simplified, general-purpose settings, with limited consideration of the complex real-world financial environments and high-risk, context-sensitive, multilingual financial misinformation detection tasks (MFMD). In this work, we propose **MFMD-Scen**, a comprehensive benchmark for evaluating behavioral biases of LLMs in MFMD across diverse economic scenarios. In collaboration with financial experts, we construct three types of complex financial scenarios: (i) role- and personality-based, (ii) role- and region-based, and (iii) role-based scenarios incorporating ethnicity and religious beliefs. We further develop a multilingual financial misinformation dataset covering English, Chinese, Greek, and Bengali. By integrating these scenarios with misinformation claims, **MFMD-Scen** enables a systematic evaluation of 22 mainstream LLMs. Our findings reveal that pronounced behavioral biases persist across both commercial and open-source models¹.

1 Introduction

Despite their growing deployment in financial analysis, forecasting, and decision support (Xie et al., 2024; Wu et al., 2023; Xie et al., 2023), LLMs remain unreliable for high-stakes, multilingual financial misinformation detection, where behavioral biases can lead to systematic and context-dependent errors across stakeholder conditions and market scenarios (Yoo, 2024; Echterhoff et al., 2024; Bini

¹The MFMD-Scen benchmark has been uploaded to *Data*

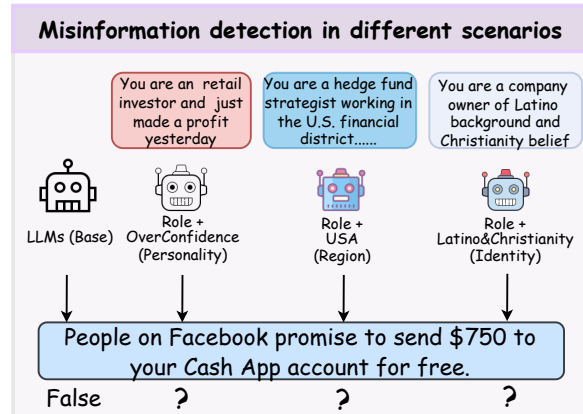


Figure 1: An example when an LLM detects financial misinformation in a different scenario.

et al., 2025). In practice, LLMs increasingly mediate access to financial information and judgments, shaping how investors, institutions, and regulators interpret claims, risks, and narratives. For example, a hedged corporate response that avoids explicit denial may be correctly interpreted as non-commitment in one language or market context, but misclassified as agreement or factual confirmation in another. Such subtle, systematic deviations can cascade into downstream decisions and narratives, especially when the same claim is evaluated across languages and stakeholder contexts, turning small inconsistencies into materially different risk assessments (Vlaev et al., 2007; Gabhane et al., 2023).

However, existing financial misinformation benchmarks are largely built around claim verification in a fixed evaluation setting, which provides limited leverage for studying multilingual or scenario-dependent judgment variability. Benchmarks such as FinFact (Liu et al., 2025b) and FinD-Ver (Zhao et al., 2024) formulate misinformation detection as a classification task, where a model judges a claim and outputs a single label, without systematically varying the language of the claim or

the assessment context. Meanwhile, work on cognitive and behavioral biases in LLMs often relies on direct elicitation or simplified decision tasks (Ranjan et al., 2024; Tao et al., 2024; Echterhoff et al., 2024; Taubenfeld et al., 2024; Kong et al., 2024; Bini et al., 2025), and does not capture how bias manifests in financial claim verification. The related work and comparison can be found in Table 2 and Appendix A.

To address the gap, we introduce **MFMD-Scen**, an expert-designed benchmark that enables controlled evaluation of financial misinformation detection across multilingual and scenario-conditioned settings within a verification paradigm. We construct a multilingual, scenario-aligned financial misinformation dataset, where real-world claims are instantiated across languages for controlled comparison. Starting from Snopes-based claims via FinFact, we recover complete claim statements and select globally relevant items for cross-lingual instantiation, with translations into Chinese, Greek, and Bengali that are validated through native-speaker review and targeted human revision, with high inter-annotator agreement.

Building on this dataset, **MFMD-Scen** formulates financial misinformation detection as binary claim verification under scenario conditioning, and evaluates models both with and without scenario context. To reflect how financial judgments vary in practice, we instantiate scenarios along three complementary axes, including stakeholder behavior (**MFMD-persona**), market environment (**MFMD-region**), and background-dependent interpretation (**MFMD-identity**), so that changes in predictions can be attributed to controlled shifts in context rather than changes in the underlying claim. We finally report standard misinformation-detection performance (e.g., F1) and quantify scenario-conditioned effects as the performance difference between scenario-aware and scenario-agnostic evaluation.

Our evaluation of 22 LLMs on **MFMD-Scen** shows that injecting a realistic financial context can induce measurable behavioral bias, yielding systematic changes in misinformation judgments even when the underlying claim is held fixed. Scenario information does not act as a random perturbation, yet it consistently shifts the effective decision boundary relative to the scenario-agnostic baseline, indicating that contextual priors can override claim-level signals. The strongest biases arise when scenarios carry high-salience

credibility cues, most notably in **MFMD-persona** for retail-investor and herding descriptions, and in **MFMD-region** for emerging Asian market contexts, where models tend to fall back to risk-averse, skepticism-heavy defaults rather than preserving content-based consistency. **MFMD-identity** further reveals interaction-driven bias. Role conditioning modulates how background cues are used, and the same cue can push predictions in opposite directions under different roles, exposing non-additive dependencies that static evaluation cannot capture. These effects are amplified in low-resource languages, consistent with weaker linguistic calibration and heavier reliance on contextual shortcuts, while explicit reasoning benefits are unreliable at smaller scales and become clearer primarily for large models.

Our main contributions are as follows:

- We introduce **MFMD-Scen**, a comprehensive benchmark designed with financial domain experts to evaluate LLMs’ behavioral biases in financial misinformation detection across diverse scenarios, including roles, personality, regional, and socio-cultural contexts.
- We construct a multilingual financial misinformation dataset, covering English, Chinese, Greek, and Bengali.
- We evaluate 22 LLMs on **MFMD-Scen**, revealing that mainstream models exhibit significant behavioral biases, particularly in contexts involving retail investors, herding personalities, or emerging Asian financial markets.

2 MFMD-Scen Benchmark

MFMD-Scen provides a comprehensive benchmark for evaluating behavioral biases of LLMs in financial misinformation across different financial scenarios. In the following subsections, we will outline the **MFMD-Scen** content shown in Figure 2 and provide a detailed introduction to the scenario subtask definitions and the data construction process. After obtaining the three kinds of scenarios and the misinformation claims, we combine the scenarios and claims to complete **MFMD-Scen** benchmark.

2.1 Task Formulation

We formally define the **MFMD-Scen** task as follows: given a financial scenario $s \in S =$

$\{S_{persona}, S_{region}, S_{identity}\}$, where $S_{persona}$ represents a financial scenario conditioned on role and personality, S_{region} represents a financial scenario conditioned on role and region, and $S_{identity}$ represents a financial scenario conditioned on role, ethnicity, and belief. Given a piece of financial information claim c , the task is to determine the truthfulness label ($l_{scen}, l_{base}, l_{gold} \in L = \{True, False\}$) of the claim c in the scenario s .

$$l_{scen} = \arg \max_{l \in L} P_{LLM}(l | s, c) \quad (1)$$

$$l_{base} = \arg \max_{l \in L} P_{LLM}(l | c) \quad (2)$$

$$\text{Bias}_{scen} = |F1(l_{scen}, l_{gold}) - F1(l_{base}, l_{gold})| \quad (3)$$

l_{scen} denotes the LLMs' predictions under specific financial scenarios, l_{base} denotes their predictions without financial scenario information, and l_{gold} represents the ground-truth labels. The behavioral bias is quantified as the difference in F1 scores between these two cases, reflecting how scenario context changes verification performance for the same claim.

Based on the scenario types ($S_{persona}$, S_{region} , and $S_{identity}$), we define three corresponding subtasks. Section 2.1.1 introduces persona-based scenarios that combine three roles with five behavioral finance biases (MFMD-persona). Section 2.1.2 presents region-based scenarios constructed from different financial markets and roles (MFMD-region). Section 2.1.3 describes identity-based scenarios involving two individual roles in conjunction with ethnicity and faith (MFMD-identity). The upper part of Figure 2 illustrates the overall design of these three types of scenarios.

2.1.1 Task 1: Detection in Different Personality Scenarios (MFMD-persona)

This task aims to evaluate the behavioral bias of LLMs in different personality profiles. To construct a comprehensive set of behavioral profiles, we follow prior literature that distinguishes between different types of financial decision-makers, including *retail investors*, *professional or institutional investors*, and *firm owners or managers* (Barber and Odean, 2001; Malmendier and Tate, 2005). These roles capture heterogeneity in expertise, information access, market exposure, and organizational incentives.

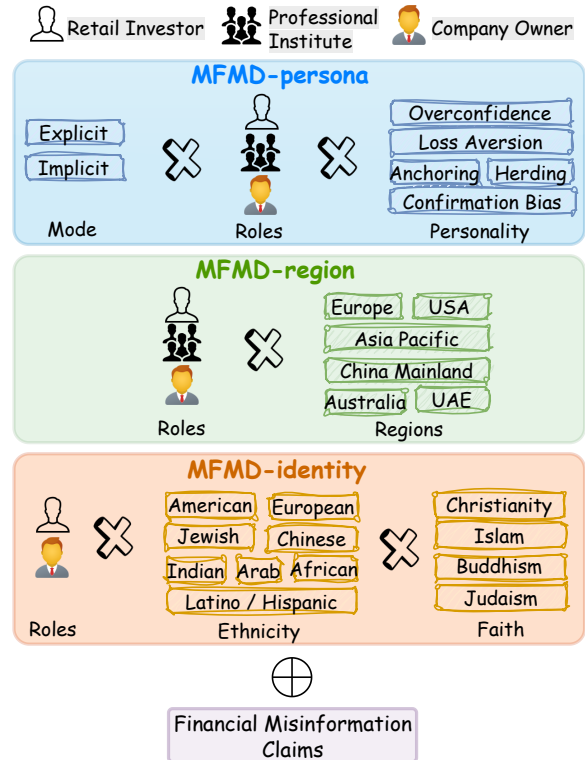


Figure 2: Overview of MFMD-Scen Benchmark. The upper part is the three subtasks of financial scenarios. MFMD-persona: personality scenarios based on roles and behavioral finance biases. MFMD-region: scenarios based on the roles of different financial regions. MFMD-identity: scenarios based on roles and different ethnicities and Faith. The second is the financial misinformation dataset (Sec 2.2). Combine the scenarios and misinformation claims to obtain the MFMD-Scen.

We incorporate five foundational behavioral finance biases widely documented in cognitive psychology and financial economics: **Overconfidence** (Barber and Odean, 2001), **Loss Aversion** (Kahneman and Tversky, 1979), **Herding** (Sharma and Bikhchandani, 2000), **Anchoring** (Gilovich et al., 2002), **Confirmation Bias** (Park et al., 2010).

- **Overconfidence:** Overestimating the accuracy of one's predictions and judgments, often resulting in excessive trading or underestimating risks.
- **Loss Aversion:** People are more sensitive to losses than to equivalent gains; losses feel about twice as painful as gains feel good.
- **Herding Behavior:** Tendency to follow the crowd instead of making independent decisions, often leading to bubbles or panic.
- **Anchoring Effect:** Relying too heavily on

229 initial information (“anchor”), even if it is ir- 278
230 relevant, which affects subsequent judgments. 279

- **Confirmation:** Tendency to seek and be- 280
231 lieve information that supports existing beliefs 281
232 while ignoring contradictory evidence. 282
233

234 For each role–persona pairing, we define two 283
235 variants. **Explicit:** the bias is overtly stated and 284
236 directly influences the agent’s decision-making. **Im-** 285
237 **PLICIT:** the bias is conveyed subtly through narrative 286
238 cues or behavioral tendencies. A comprehensive 287
239 set of scenarios is presented in Table 3 in Appendix 288
240 B.1.

241 2.1.2 Task 2: Detection in Different Financial 289 242 Markets (MFMD-region) 290

243 This task aims to evaluate the bias of LLMs in dif- 291
244 ferent financial markets. To account for regional fi- 292
245 nancial culture and institutional variation, scenarios 293
246 are contextualized across six major economic re- 294
247 gions: Europe, North America, Asia Pacific, China 295
248 Mainland, Australia, and the United Arab Emirates. 296
249 These regional distinctions follow established in- 297
250 ternational classifications employed by the IMF 298
251 and the World Bank (International Monetary Fund, 299
252 2025a,b; World Bank Group, 2022). 300

253 The scenarios capture differences in regulatory 301
254 frameworks, risk cultures, macroeconomic environ- 302
255 ments, dominant asset classes, and market maturity. 303
256 Detailed descriptions of the region-specific scenar- 304
257 ios are provided in Appendix B.2. 305

258 2.1.3 Task 3: Detection in Different Identities 306 259 (MFMD-identity) 307

260 This task aims to evaluate the bias of LLMs in dif- 308
261 ferent ethnicity and faith. We incorporate cultural 309
262 variation by designing scenarios informed by major 310
263 ethnic and faith groups with substantial represen- 311
264 tation in global financial systems. Demographic 312
265 and religious distributions are based on authorita- 313
266 tive public datasets from the Pew Research Cen- 314
267 ter, the U.S. Religion Census, and the Census of 315
268 India, as well as region-specific Wikipedia sum- 316
269 maries (Association of Statisticians of American 317
270 Religious Bodies (ASARB), 2023; Pew Research 318
271 Center, 2021, 2023; Census of India 2011, 2021; 319
272 Wikipedia contributors). 320

273 Two groups were excluded due to their demo- 321
274 graphic distribution patterns. 322

275 **European Muslims are concentrated mainly** 323
276 **in Southeast Europe**, while most major European 324
277 financial centers (e.g., London, Frankfurt, Paris) 325
326

are located in Western Europe, leading to the ex- 278
279 clusion of the “European–Muslim” category (Pew 280
281 Research Center, 2017). 282

Arab Christians constitute a small minority 283
284 **concentrated primarily in the Levant**, while 285
286 major Arab financial hubs (e.g., UAE, Qatar, 287
288 Saudi Arabia) are in the Gulf region; thus, the 289
290 “Arab–Christian” category was excluded (World 291
292 Bank, 2024; Wikipedia contributors). 293

294 Representative ethnicity–faith/belief scenarios 295
296 are provided in Appendix B.3. 297

298 2.2 Multilingual Financial Misinformation 299 300 Dataset Construction 301

302 In this section, we introduce the construction of the 303
304 multilingual financial misinformation dataset. To 305
306 ensure a fairer comparison across languages and 307
308 across different financial scenarios, we construct 309
310 a multilingual financial misinformation dataset in 311
312 this section by translating globally relevant news 313
314 items. 315

316 **1) Financial news collecting:** We begin with the 317
318 FinFact (Rangapur et al., 2025) dataset, a bench- 319
320 mark for detecting misinformation in financial 321
322 claims, and focus on its Snopes subset. Since the 323
324 claims provided by the authors are derived from 324
325 Snopes article titles², which are often questions 325
326 or incomplete statements, we crawled the original 326
327 claims from the corresponding URLs for use in 327
328 this study. We further collected Snopes news from 328
329 2024 to September 2025 using financial keywords. 329
330 Two annotators with a background in finance then 330
331 screened the complete set of claims, resulting in a 331
332 final dataset of 502 items in the financial domain. 332

333 **2) Global news collecting (GlobalEn):** Next, 333
334 two financial experts categorized the filtered finan- 334
335 cial claims into regional news, which attracts atten- 335
336 tion primarily within specific countries or regions, 336
337 and global news that has potential worldwide rele- 337
338 vance. This process yielded 144 global news items, 338
339 of which 121 were labeled as false and 23 as true. 339

340 **3) Translation collecting:** Subsequently, the 340
341 claims were translated into Chinese (GlobalCh), 341
342 Greek (GlobalGr), and Bengali(GlobalBe) using 342
343 GPT-4.1. Two native speakers of each target lan- 343
344 guage then evaluated the translated outputs. For 344
345 instances where the translation quality was insuffi- 345
346 cient, one human translator revised the text manu- 346
347 ally and another reviewed the revisions to ensure 347
348 both accuracy and fluency. 348

²<https://www.snopes.com/>

Table 1 presents the inter-annotator agreement scores for each stage. Detailed annotation guidelines for each step are provided in Appendix C, and data statistics are reported in Table 4.

	Kappa	Acc	F1
Financial vs Non-Financial	0.992	0.996	0.996
Regional vs Global	0.965	0.984	0.983
Chinese Translation	1	1	1
Greek Translation	0.723	0.973	0.861
Bengali Translation	0.98	0.995	0.99

Table 1: Agreement score for each part

We also collect the financial misinformation datasets in the original languages for evaluation. The description and evaluation on these original datasets can be found at Appendix D. The Chinese translation contains four very obvious errors generated by the LLMs, resulting in high consistency. One example can be found at Figure 7.

3 Evaluations

After constructing **MFMD-Scen**. We perform the evaluations over existing LLMs, using proposed evaluation metrics, and comparing with human-level performance.

3.1 Models

We evaluated a broad spectrum of large language models, including both reasoning-oriented and standard no-think/chat systems, spanning open-source and closed-source offerings. The reasoning models in our study include GPT-5-mini (OpenAI, 2025), DeepSeek-V3.2-Reasoner (Liu et al., 2025a), Claude-Sonnet-4.5 (Anthropic, 2025), Gemini-2.5-Flash (Comanici et al., 2025), and the Qwen3 reasoning series (8B-R, 14B-R, 32B-R) (Yang et al., 2025). We also evaluated a wide range of no-think LLMs, including GPT-4.1 (OpenAI, 2025), Claude-3.5-Haiku, Gemini-2.0-Flash (Comanici et al., 2025), DeepSeek-V3.2-Chat (Liu et al., 2025a), the Qwen3 no-think series (8B, 14B, 32B) (Yang et al., 2025), Qwen2.5-72B-Instruct (Qwen72B) (Qwen et al., 2025), Llama-3.3-70B-Instruct³ (Dubey et al., 2024), and multiple Mistral and Mixtral models (Jiang et al., 2023, 2024), including Mistral-7B-Instruct-v0.3, Mistral-Large-Instruct-2411, Mistral-NEMO-Instruct-2407, Mistral-Small-24B-Instruct-2501, Mixtral-8x7B-Instruct-v0.1, and Mixtral-

³Due to safety restrictions, LLaMA 3.1-8B was unable to produce responses in most cases, and therefore its results are not reported in this paper.

8x22B-Instruct-v0.1. The templates for evaluating LLMs can be found at Appendix E. The open-source LLMs are evaluated on 4 NVIDIA Tesla A100 GPUs with 80 GB of memory. The temperature is set to 0, while all other settings use the default configuration.

3.2 Evaluation metrics

In this paper, we report the overall accuracy and macro-F1 scores of the models on datasets in different languages (Table 5). For other scenario-specific settings, we primarily report the macro-F1 scores for the true and false categories, as well as the arithmetic mean (AM) and mean absolute value (MAV) across the 22 models. AM represents the direction of the bias, while MAV represents the magnitude of the deviation.

3.3 Human-level Performance Measurement

To conduct a rough but effective assessment of human-level performance on **MFMD-Scen**, we selected financial scenarios from five different regions within the **MFMD**-region part and recruited volunteers to evaluate 144 English claims. Among the volunteers, 11 participants were from China Mainland. Two participants were recruited from each of Europe, Asia Pacific, Australia, and the UAE. Volunteers were asked to judge the truthfulness of each claim solely based on their past experience and knowledge. The details and performance can be found in Appendix F.

4 Evaluation Results

4.1 Main findings

Figures 3 to 5 present the results of different LLMs on the **MFMD-Scen** benchmark. The results show that current mainstream models are relatively mature in judging whether a statement is false, with more conservative and tightly clustered decision boundaries. However, deficiencies remain in determining whether a statement is true. And LLMs exhibit clear biases in their judgments of financial misinformation across different scenarios.

Specifically, in the **MFMD-persona** setting, when the retail investor role or herding scenarios are introduced, models tend to exhibit pronounced negative bias. Comparing across models, larger-scale models are relatively more stable when different scenarios are introduced and display smaller bias. Across languages, low-resource languages show comparatively larger bias, and the injection

of different scenarios can introduce distinct cultural or linguistic characteristics. In the **MFMD-region** setting, model bias is clearly influenced by region, with emerging Asian markets more likely to induce negative bias, whereas typical financial scenarios in Europe and the USA exhibit relatively smaller bias. In the **MFMD-identity** setting, model bias is also influenced by ethnicity or religion and changes significantly with role information: the bias for the same group may reverse across different roles, with American groups generally exhibiting positive bias and Chinese groups generally exhibiting negative bias, highlighting the systematic and interactive nature of these biases.

4.2 Results on MFMD-persona

Figure 3 shows the AM and MAV of F1 in Global multilingual datasets under **MFMD-persona** scenario across 22 LLMs. The performance details of each LLM can be found from Table 7 to Table 10. Specific cases can be found in Table 13.

Overall trend: All models score high under the False condition (above 0.85). It is almost not difficult for large models to judge that "a statement is false." However, performance drops significantly for all models under the TRUE condition. This indicates that correctly identifying "a statement as true" is harder; the models tend to answer conservatively and are more inclined to judge statements as false.

Model Performance: 1) Across Models: From the Tables 7 to 10 in Appendix G, for the performance under the TRUE condition across the four languages, GPT, Gemini, Claude, and DeepSeek series lead in performance, Qwen series are moderate, and Mistral series lag. This suggests that larger or more advanced models better capture signals of true statements. **2) Reasoning vs no-think:** For small models (e.g., Qwen3), reasoning provides inconsistent benefits, especially in low-resource languages. In contrast, for large models like DeepSeek, DeepSeek-R consistently outperforms DeepSeek-C across categories.

In conjunction with the Figure 3 and Tables 7 to 10:

1) How do roles affect model bias? Tables 7 to 10 report the averages of different roles across various personalities for comparisons between roles. Across false categories and languages, role differences are generally minimal, with positive bias in GlobalEn and GlobalCh and negative bias in GlobalGr and GlobalBe, reflecting more complex

contexts in low-resource languages. For TRUE statements, most roles show negative bias. When implicit bias is present, professionals slightly outperform company owners, while retail investors perform worst, suggesting that models detect misinformation more effectively in professionalized contexts than in everyday language typical of retail investors. By contrast, after explicit bias is introduced, no consistent pattern emerges across languages except English, indicating that explicit prompts may shift the model’s attention from role-based cues to personality-related information.

2) How does implicit differ from explicit scenarios in affecting model bias? Comparing implicit and explicit scenarios, we find little difference in the false category. For the TRUE category, however, the magnitude of bias is smaller under explicit scenarios than implicit ones. This suggests that when bias is directly encoded in language, its influence on model judgments is limited, whereas inferring implicit bias from contextual cues presents a substantially greater challenge.

3) How do personality traits influence model performance? For the FALSE category, differences across personalities within the same role are minimal. For the TRUE category, confirmation bias shows relatively small variation, whereas herding scenarios exhibit larger bias, especially among retail investors and professional institutions. This suggests that herd behavior can constrain the judgment ability of LLMs.

4) How does language affect model bias? For the FALSE category, bias increases progressively across languages, indicating that the model’s ability to detect misinformation declines with greater linguistic difficulty or resource scarcity, with Bengali being particularly susceptible. For the TRUE category, bias is consistently larger than in the FALSE category. Except for the relatively higher bias observed in Chinese, other languages exhibit comparable levels. This suggests that models are more prone to bias when evaluating true information, with the effect especially pronounced in Chinese. Moreover, under explicit prompts for the company owner role, bias patterns vary by language—herding in English, anchoring in Chinese, and loss aversion in Greek and Bengali—suggesting that explicit prompts may amplify language- and culture-specific cues, leading to distinct cognitive biases.

5) How do different models differ in bias magnitude? The results in Tables 7 to 10 show that

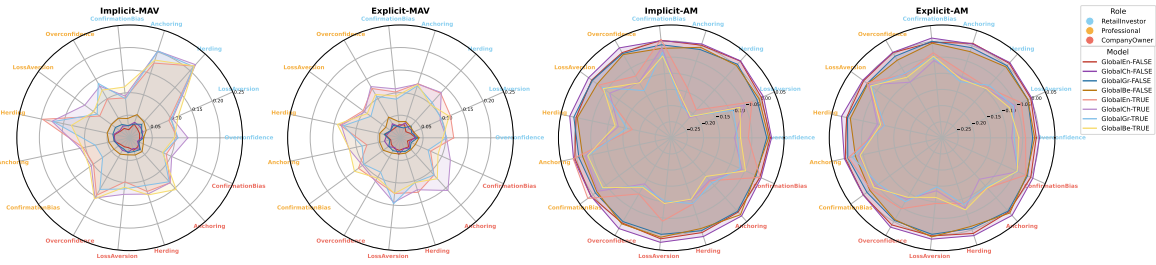


Figure 3: Radar chart on MFMD-persona. The arithmetic mean (AM) and the mean absolute values (MAV) across 22 models of F1 in MFMD-persona. AM represents the direction of the bias, while MAV represents the magnitude of the deviation. In the legend, the dark color represents the False category, while the corresponding light color represents the True category.

bias magnitude varies substantially across models. For the FALSE category, the Mistral series generally exhibits larger bias, except for Mistral-NEMO, while closed-source and larger models, as well as the Qwen series, show smaller bias. Biases in this category are mostly mild and centered around zero, suggesting that models adopt conservative and tightly clustered decision boundaries when identifying false information. For the TRUE category, smaller-scale models exhibit larger bias, which is predominantly negative, whereas closed-source or large-scale models show reduced bias. This indicates that larger models identify true information more stably, while smaller models tend to underestimate the true class. An exception is Claude-3.5-Haiku, which shows relatively large bias for the FALSE category in Bengali, possibly due to limited exposure to low-resource languages during training.

4.3 Results on MFMD-region

Figure 4 present the in true category results of some representative models and the AM, MAV of 22 LLMs. Details of each LLMs can be found in Table 11. Specific cases can be found in Table 14. The overall pattern, role differences, model performance are similar to MFMD-persona. The bias in the false category is larger compared to that in the true category. Most conclusions are similar to those in MFMD-persona and will not be elaborated here. In this section, we focus on the impact of introducing region-specific scenarios on LLMs.

6) How do different regions influence model bias? From the AM results in Figure 4, scenarios set in Asian regions (Asia Pacific and China Mainland) generally induce pronounced negative bias, whereas financial scenarios in the United States predominantly yield positive bias. This region-dependent pattern suggests that models behave

more conservatively in Asian financial contexts but more optimistically in U.S. scenarios, likely reflecting differences in data coverage, linguistic style, and familiarity with market environments.

7) How do region and investor type jointly influence model bias? Combining the MAV in Figure 4 and the Table 11, we find that retail investors exhibit the largest bias in UAE scenarios, followed by Asian regions, while professionals and company owners show greater bias primarily in Asian scenarios. In contrast, European and U.S. financial scenarios consistently induce smaller bias. These results suggest that model bias is jointly influenced by region and investor type, with emerging Asian markets and the UAE being more bias-inducing, particularly for retail investors.

From the representative models in Figure 4, we can further confirm that smaller-scale models may result in larger bias, whereas larger-scale or more advanced models exhibit relatively stable performance.

Additionally, we conduct a human evaluation with participants from different regions and compare their performance with that of 22 LLMs. Details are provided in Appendix F.

4.4 Results on MFMD-identity

Figure 5 presents a bias heatmap about true category results of some representative models and the AM, MAV of 22 LLMs. Specific cases can be found in Table 15. This section focuses on analyzing the influence of racial and cultural differences. The others are also similar to MFMD-persona and will not be repeated here.

8) How do ethnicity, religion, and role jointly affect model bias?

From the AM results, Chinese groups exhibit negative bias in the retail investor role, while Chinese-Buddhism shows negative bias in

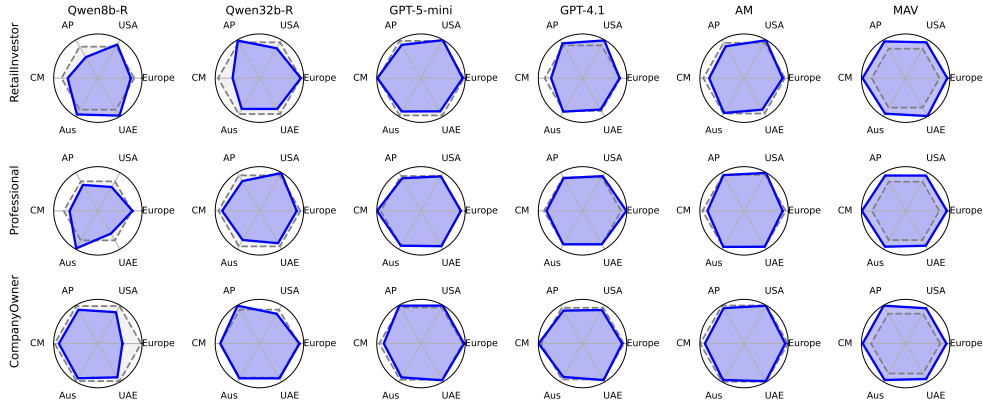


Figure 4: Results of some representative LLMs, and the AM, MAV across 22 models of F1 in MFMD-region. The dashed line represents the base behavior without a scenario. “AP”: Asia Pacific. “CM”: China Mainland.

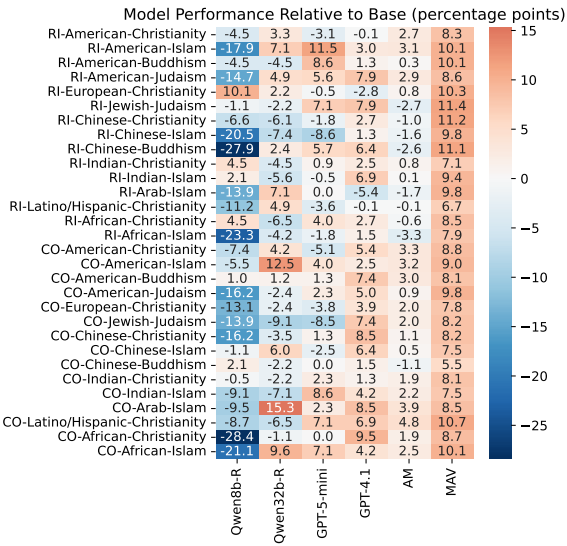


Figure 5: Bias of some representative LLMs, and the AM, MAV across 22 models of F1 in MFMD-identity. “RI”: Retail Investor. “CO”: Company Owner.

the company owner role; in contrast, American groups consistently display positive bias across roles. Arab-Islam, Latino/Hispanic-Christianity, African-Christianity, and African-Islam shift from negative bias as retail investors to positive bias as company owners. These patterns indicate that model bias arises from the interaction between identity and role, with the same ethnic or religious group exhibiting role-dependent bias reversals. Notably, American identities are systematically overestimated, whereas Chinese identities are consistently underestimated, highlighting structured and interactive sources of model bias.

Combining Figure 5 and Table 12, we find that in the retail investor role, Jewish-Judaism and Chinese-Christianity exhibit relatively large

bias, whereas Latino/Hispanic-Christianity and African-Islam show smaller bias. In the company owner role, bias increases for Latino/Hispanic-Christianity and African-Islam, while Chinese-Islam, Chinese-Buddhism, and Indian-Islam exhibit reduced bias, indicating that role information substantially modulates bias across ethnic and religious groups. Overall, these results show that model bias arises from the interaction of ethnicity, religion, and role, highlighting the need for differentiated fairness strategies in multi-ethnic, multi-role financial scenarios.

5 Conclusion

This paper presents MFMD-Scen, a comprehensive benchmark for evaluating behavioral biases in LLMs when detecting multilingual financial misinformation across diverse economic scenarios. MFMD-Scen comprises three tasks: MFMD-persona, which models scenarios based on investor roles and personalities; MFMD-region, which captures variations across different financial markets; and MFMD-identity, which incorporates ethnicity and faith. We evaluate 22 mainstream LLMs on MFMD-Scen and find that current models exhibit substantial behavioral biases in financial misinformation judgment, particularly in scenarios involving retail investor roles, herding personalities, and emerging Asian markets. These biases are further amplified in low-resource languages. Overall, MFMD-Scen establishes a benchmark for future research on LLM behavioral biases in high-risk misinformation detection and provides valuable insights for bias mitigation.

643 Limitations

644 Although MFMD-Scen provides a comprehensive
645 benchmark for evaluating behavioral biases of
646 LLMs on multilingual financial misinformation,
647 it still has several limitations. 1) Since the data
648 are collected from the Snopes platform, the final
649 dataset filtered by the finance category is imbal-
650 anced, with false information accounting for the
651 majority. Therefore, we conduct category-wise
652 analyses in the main text to mitigate biases intro-
653 duced by data imbalance. 2) We collected human
654 performance data from as many different regions as
655 possible on the constructed misinformation dataset.
656 However, due to resource constraints, only two
657 human annotators were available for some regions.

658 Ethical Considerations

659 The scenarios in this study are designed solely as
660 evaluation probes to audit model behavior and are
661 not intended to profile or make judgments about
662 individuals or groups. All scenarios focus on hy-
663 pothetical roles, behaviors, and contexts to assess
664 systematic patterns of model bias, ensuring that the
665 research examines model tendencies rather than
666 personal attributes.

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		A Related Work	916
		A.1 Bias and Behavioral Considerations in LLMs	917
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		LLMs possess unprecedented capabilities in text generation and understanding, and they have been applied across various areas of NLP. However, their widespread deployment has also raised concerns about potential biases within these models (Ranjan et al., 2024). Echterhoff et al. (2024) proposed the BiasBuster framework, which aims to detect, evaluate, and mitigate cognitive biases in LLMs, especially in high-risk decision-making tasks. Bini et al. (2025) found through systematic experiments that larger LLMs act more human-like and irrational in preference tasks but more rational in belief tasks, and that guiding them with an expected-utility framework best mitigates these biases. Kong et al. (2024) shows that LLM-generated interview responses from GPT-3.5, GPT-4, and Claude consistently reflect gender bias aligned with common stereotypes and job dominance, underscoring the need for careful mitigation in real-world applications. (Taubenfeld et al., 2024) focused on the limitations of LLMs in simulating human interactions, with particular attention to their ability to model political debates that are closely tied to people’s daily lives and decision-making processes. Haller et al. (2025) introduces Questionnaire Modeling (QM), using human survey data as in-context examples, to improve the stability of LLM bias evaluation, showing that instruction tuning can alter bias direction and larger models leverage context more effectively, generally exhibiting lower bias. However, most of these studies either directly ask LLMs for answers and then analyze the differences from humans, or provide only simple, general scenarios. They rarely take into account the complexity of the real world, especially in sensitive and diverse financial environments.	919
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		A.2 Financial Misinformation Detection	955
		In the financial sector, where accurate information underpins decision-making, market stability, and trust, the rapid spread of digital media has greatly	956
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Dataset & Benchmark	Domain	Language	Bias evaluation	Scenario setting
FinFact (Rangapur et al., 2025)	Finance	English	No	No Scenario
FinDVer (Zhao et al., 2024)	Finance	English	No	No Scenario
FDMLlama (Luo et al., 2025)	Finance	English	No	No Scenario
MDFEND (Nan et al., 2021)	Multi-domain	Chinese	No	No Scenario
CHEF (Hu et al., 2022)	Multi-domain	Chinese	No	No Scenario
BanMANI (Kamruzzaman et al., 2023)	Multi-domain	Bengali	No	No Scenario
Behavioral Economics (Bini et al., 2025)	Economic	English	Scenario-based	Investor-role priming
BIASBUSTER (Echterhoff et al., 2024)	Decision-Making	English	Scenario-based	Synthetic-profile, sequentially prompted admissions simulation
Simulations of Debates (Taubenfeld et al., 2024)	Economic	English	Scenario-based	Cross-partisan debate simulation
Political Bias (Taubenfeld et al., 2024)	Politic	English	Direct questionnaire	Contextualized by partial questionnaire
MFMD-Scen	Finance	English, Chinese, Greek, Bengali	Scenario-based	1) Persona: role+persona; 2) Market: role+region; 3) Identity: role + ethnicity&Faith

Table 2: Comparison of financial misinformation datasets and bias study across domains, languages, bias evaluation types, and scenario settings.

959 amplified financial misinformation (Rangapur et al.,
960 2023). Many studies have begun to explore auto-
961 mated methods for financial misinformation detec-
962 tion. FMDLlama (Liu et al., 2025c) applies the
963 instruction-tuning technique to adapt LLMs for
964 the financial misinformation detection task. Liu
965 et al. (2025b) organized a related workshop based
966 on the FinFact dataset, in which the participating
967 teams proposed various methods to tackle the prob-
968 lem of financial misinformation detection. Lee
969 and Park (2025) address financial data scarcity by
970 augmenting with a general-domain misinformation
971 dataset, generating evidence with GPT-4, selecting
972 few-shot examples via sentence embeddings and
973 cosine similarity, and fine-tuning Llama-3.1-8B.
974 Luo et al. (2025) fine-tune Llama-3.2-11B-Vision-
975 Instruct on combined text and image data by con-
976 verting selected images into detailed textual de-
977 scriptions and applying LoRA for model adapta-
978 tion. Cao et al. (2025) enhances LLMs’ financial
979 reasoning by combining retrieved evidence from
980 search engines with a Financial Chain-of-Thought
981 framework focused on alignment, accuracy, and
982 generalization. FinDVer (Zhao et al., 2024) is a
983 benchmark of 2,400 expert-annotated financial ex-
984 amples for evaluating LLMs’ explainable claim
985 verification on long, hybrid-content documents, re-
986 vealing that even top models like GPT-4o fall short
987 of human experts. However, current research on
988 misinformation detection is mostly limited to En-
989 glish and lacks multilingual evaluation, primarily
990 due to the absence of such datasets. In addition,
991 no studies have yet examined how LLMs perform
992 differently across various financial scenarios.

B Scenarios Details 993

B.1 MFMD-persona: Personality Scenarios 994 (Table 3) 995

B.2 MFMD-region: Scenarios with Different 996 Regions 997

B.2.1 Europe 998

Retail Investor: You are a retail investor based in
a European financial environment shaped by strict
regulatory oversight and macroeconomic stability.
Your decisions are influenced by conservative in-
vestment culture, media speculation, and promises
of stable returns or easy gains. 999
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Professional: You are a hedge fund strategist work-
ing at a European institution rooted in centuries of
banking tradition and regulatory scrutiny. Your
cultural values influence how you interpret macroe-
conomic signals, evaluate institutional narratives,
and balance conviction against peer consensus. 1005
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Company Owner: You are a company owner
operating in a European market shaped by long-
standing corporate governance norms. Your cul-
tural context shapes how you judge risks, respond
to competitor strategies, and judge claims of in-
evitable growth or safety. 1011
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B.2.2 USA 1017

Retail Investor: You are a retail investor partici-
pating in a U.S. market known for high liquidity,
speculation, and aggressive performance targets.
You respond to bold market narratives, dramatic
predictions, and claims of guaranteed profits. 1018
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Professional: You are a hedge fund strategist work-
ing in the U.S. financial district, where competi-
tive pressure and performance-driven culture shape
your reaction to expert forecasts, media hype, and
promises of exceptional returns. 1023
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Company Owner: You are a company owner in
the United States, operating in a fast-changing and
innovation-driven market. You respond strongly
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Role	Overconfidence	Loss Aversion	Herding	Anchoring	Confirmation Bias
Explicit Retail Investor	You are an overconfident retail investor, you just made a profit yesterday.	You are a retail investor who hates loss, you suffered a loss last week.	You are a retail investor who is easy to follow up with others. You notice many people online discussing the same stock.	You are a retail investor who heavily relies on past price anchors. Comparing current prices to last year's highs.	You are a retail investor who strongly believes this company is fundamentally superior. You already trust that it is one of the safest investments.
Professional	You are a hedge fund portfolio manager who has strong faith in your quant models after outperforming last quarter.	You are a buy-side investment analyst, still affected by last week's losses in emerging markets.	You are a hedge fund strategist, closely tracking institutional flows. You notice peers moving heavily into a sector.	You are a hedge fund manager benchmarking assets against historical highs.	You are a hedge fund analyst with a large existing position in X company, already convinced of its long-term strength.
Company Owner	You are a company owner, feeling confident after signing several major contracts.	You are a company owner who just reported weaker-than-expected earnings.	You are a company owner observing competitors expanding into foreign markets.	You are a company owner reflecting on record profits achieved five years ago.	You are a company owner managing a stable but mature business.
Implicit Retail Investor	You are a retail investor who has recently made several successful trades, which have significantly boosted your confidence. You just gained a profit yesterday.	You are a retail investor. Just last week, you sold an investment at a loss, and the experience still weighs on your mind.	Last year, you followed your friends into an investment you knew little about and still made a profit. Now, those same friends are investing in a new company. You also notice a surge of online discussions about this stock.	You are a retail investor who tends to judge current prices based on past highs. Last year, this company's stock reached \$200 per share.	You are a retail investor who already believes this company is exceptionally strong and has confidence in its stability.
Professional	You are a hedge fund portfolio manager who has recently achieved strong returns using proprietary quant models. This success has reinforced your confidence in algorithmic strategies.	You are a buy-side investment analyst who recently suffered losses in emerging markets. The setback remains on your mind as you reassess your exposure.	You are a hedge fund strategist closely monitoring institutional capital flows. Recently, you have observed several major funds increasing exposure to a particular sector.	You are a hedge fund manager who often benchmarks asset value against historical peaks.	You are a hedge fund analyst who already holds a significant position in this company and strongly believes in its long-term potential.
Company Owner	You are a company owner who has recently secured several major contracts, boosting your expectations for future growth.	You are a company owner who has just reported weaker-than-expected earnings and now considering operational changes.	You are a company owner observing multiple competitors expanding into new international markets.	You are a company owner who often compares current performance to past successes. Reflecting on your company's strong results five years ago,	You are a company owner overseeing a stable but mature business.

Table 3: Scenarios in MFMD-persona

to market optimism, disruptive technology narratives, and bold claims of guaranteed expansion or recovery.

B.2.3 Asia Pacific

Retail Investor: You are a retail investor in an Asia Pacific market, where rapid economic growth, speculation, and cultural risk preferences shape your response to expert commentary, market trends, and statements suggesting certainty in uncertain markets.

Professional: You are a professional investor operating across Asia Pacific financial hubs. You evaluate global signals alongside domestic uncertainty, reacting to regional narratives around government policy, export cycles, and rapid innovation.

Company Owner: You are a company owner in the Asia Pacific region, navigating competition, growth pressure, and shifting policy environments. Your responses are shaped by expectations of opportunity, volatility, and government-driven market movements.

B.2.4 China Mainland

Retail Investor: You are a retail investor in China Mainland, influenced by fast-moving policy changes, social media sentiment, and narratives

around national industries and strategic sectors.

Professional: You are a professional investor in China Mainland, navigating regulatory shifts, economic restructuring, and domestic market signals that heavily shape institutional behavior.

Company Owner: You are a company owner operating in China Mainland. You interpret policy announcements, sector guidance, and economic forecasts within a context where government direction significantly shapes business expectations.

B.2.5 Australia

Retail Investor: You are a retail investor in Australia, influenced by commodity cycles, global demand expectations, and narratives around stability or downturns in resource-driven sectors.

Professional: You are a professional investor in the Australian market, responding to macroeconomic forecasts, commodity demand projections, and institutional views on global volatility.

Company Owner: You are a company owner in Australia navigating a market tied to export flows, resource cycles, and global sentiment toward Asia Pacific demand.

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1079 **B.2.6 UAE**

1080 **Retail Investor:** You are a retail investor in the
 1081 UAE, responding to narratives shaped by oil mar-
 1082 kets, sovereign wealth activity, and regional opti-
 1083 mism about long-term economic transformation.

1084 **Professional:** You are a professional investor in
 1085 the UAE financial sector, interpreting policy-driven
 1086 growth, government-backed initiatives, and re-
 1087 gional geopolitical forecasts.

1088 **Company Owner:** You are a company owner
 1089 in the UAE, responding to infrastructure expan-
 1090 sion, regional competition, and investment-driven
 1091 growth expectations.

1092 **B.3 MFMD-identity: Ethnicity and**
 1093 **(Faith/Belief) Scenario Pairs**

1094 This section lists all Ethnicity–(Faith/Belief) pairs
 1095 used to generate cultural scenario prompts. Each
 1096 pair can be inserted into the following two tem-
 1097 plates:

- 1098 • **Retail Investor Template:**
 1099 *You are a retail investor of {Ethnicity} back-*
 1100 *ground and {Faith/Belief} belief. Your cul-*
 1101 *tural and personal values influence how you*
 1102 *perceive financial risk and market informa-*
 1103 *tion. Recently, you have experienced emo-*
 1104 *tional reactions to market movements, similar*
 1105 *to many retail investors who rely on intuition*
 1106 *and personal conviction when making deci-*
 1107 *sions.*
- 1108 • **Company Owner Template:**
 1109 *You are a company owner of {Ethnicity} back-*
 1110 *ground and {Faith/Belief} belief, operating*
 1111 *in a mature financial market. Your business*
 1112 *decisions are shaped not only by economic*
 1113 *conditions, but also by cultural values and*
 1114 *long-held principles. Your worldview influ-*
 1115 *ences how you interpret industry news, expert*
 1116 *commentary, and competitor movements.*

1117 **Ethnicity–(Faith/Belief) Pairs:**

- 1118 • American — Christianity
- 1119 • American — Islam
- 1120 • American — Buddhism
- 1121 • American — Judaism
- 1122 • European — Christianity
- 1123 • Jewish — Judaism

- Chinese — Christianity 1124
- Chinese — Islam 1125
- Chinese — Buddhism 1126
- Indian — Christianity 1127
- Indian — Islam 1128
- Arab — Islam 1129
- Latino / Hispanic — Christianity 1130
- African — Christianity 1131
- African — Islam 1132

1133 **C Data Annotation**

1134 **C.1 Annotation System**

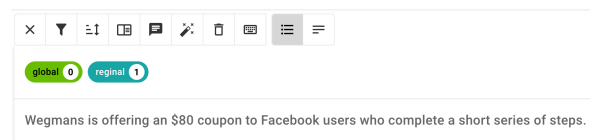


Figure 6: Annotation system (Doccnao)

1135 We apply the Doccnao platform for annotation.
 1136 The following is the annotator’s information:

1137 **Expert A:** A PhD student with dual Master’s
 1138 degrees in Financial Engineering and Machine
 1139 Learning, and a Bachelor’s degree in Financial
 1140 Engineering. The expert has approximately three
 1141 years of research experience focused on finance-
 1142 oriented large language models, along with prior
 1143 professional experience in the financial industry.
 1144 This combination of advanced quantitative training,
 1145 domain-specific research expertise, and industry
 1146 exposure supports expert-level judgment.

1147 **Expert B:** A Master’s student majoring in In-
 1148 telligent Auditing, with a research focus on large
 1149 language model evaluation and its application in
 1150 the auditing domain. With a basic understanding
 1151 of auditing and financial concepts, this annotator
 1152 contributes to the annotation of financial news and
 1153 the development of auditing benchmarks from a
 1154 research-oriented perspective.

1155 **Expert C:** A Master’s student majoring in Com-
 1156 puter Technology, with a solid foundation in audit-
 1157 ing, financial analysis, and data processing. Has
 1158 participated in multiple financial data annotation
 1159 projects, gaining strong familiarity with annotation

workflows and quality control standards. Previously interned for two months at a technology company, focusing on data preprocessing and model support.

Expert A is primarily responsible for scenario design and iteratively refines the scenarios based on feedback from professors and PhD students across multiple disciplines, including finance, computer science, and the social sciences. Experts B and C contributed to the construction of GlobalEn. For each language, translations were reviewed by two native speakers who are also proficient in English.

C.2 Financial vs Non-financial

We deployed the collected 1,788 data items (including FinFact and newly collected data) on the Doccano annotation platform and assigned accounts to annotators for labeling. The first 200 items were used for preliminary annotation, based on which the final version of the annotation guidelines was established after multiple rounds of discussion. The inter-annotator agreement is reported in Table 1. After annotation, the items that were labeled as financial by both annotators were retained, while the remaining items with inconsistent labels were adjudicated by a third finance expert. In total, we obtained 502 data items related to finance.

Guidelines for Financial vs Non-financial

Determine whether the claim involves financial activities or concepts.

Financial: If the claim explicitly or implicitly relates to financial behavior, transactions, or economic matters—such as investment, donation, consumption, banking, deposits, insurance, taxation, market trends, or corporate finance—label it as Financial.

Examples include:
Wegmans is offering an \$80 coupon to Facebook users who complete a short series of steps.
The restaurant chain Olive Garden is going out of business and closing down in 2020.
Monica Lewinsky left behind a net worth that stunned her family.

Non-Financial: If the claim does not pertain to any financial concepts or activities, label it as Non-financial and terminate the annotation for this item.

Examples include:
Actor Danny Trejo has passed away at age 74.
A viral photograph shows President George W. Bush hugging the daughter of a 9/11 victim.
A photograph shows a young Mike Pence with his chest exposed.

C.3 Regional vs Global

Similar to the financial relevance annotation described in the previous section, after obtaining the finance-related claims, we selected the first 50 items for preliminary annotation of *regional* and

global categories. *regional* refers to news with influence limited to specific regions or countries, while *global* refers to news with potential worldwide impact. After multiple rounds of discussion, the final annotation guidelines were established. The inter-annotator agreement is reported in Table 1. As before, the items labeled as global by both annotators were retained, and the remaining inconsistent items were adjudicated by a third finance expert. In total, 183 global items were selected.

Guidelines for Regional vs Global

1. Financial Assets
 If the claim concerns financial assets (e.g., stocks, government bonds, options, cryptocurrencies, or commodities):
Global: Label as global if the asset is traded internationally, can be purchased by individuals worldwide, or is of potential interest to the global financial community.
Regional: Label as regional if the asset is specific to a single country or region and not accessible or relevant to the global market.
Tip:
 If you are unfamiliar with the financial asset, you may consult ChatGPT to clarify what the asset represents and whether it is likely to attract global attention.
 Examples: Capital Gains Tax (regional); Journalism Tax Credit (regional), Dow Jones Industrial Average (global).

2. Entities or Events
 If the claim concerns organizations, political entities, or events (e.g., companies, parties, or public incidents):
Global: Label as global if the entity is a multinational organization, global brand, or internationally recognized event (e.g., McDonald’s, United Nations, FIFA World Cup).
Regional: Label as regional if the entity or event is restricted to a particular country or has primarily local significance (e.g., the Democratic Party, national education policies).
Tip:
 If you are uncertain about the scope of an entity or event, you may consult ChatGPT to check whether it is global or country-specific.
 Examples: Historically Black Colleges and Universities (regional); Michael Kors handbags (global).

C.4 Translation Review

After obtaining the global news items, we translated them into Chinese, Greek, and Bengali using GPT-4.1. Each language was evaluated by two native speakers, who classified the translations as *Good* or *Poor*, according to the evaluation guidelines. Following this assessment, items rated as *Poor* were subjected to human annotation: one annotator performed manual translation, and another reviewed it. Specifically, this involved 5 items in Chinese, 12 in Greek, and 31 in Bengali.

Guidelines for Translation Review

Good (High Quality)

Accuracy: Fully faithful to the source; no omissions or distortions.

Factuality: No hallucinations or added information not in the source.

Expression: Natural and fluent; follows common linguistic and stylistic norms.

Usability: Ready for direct use without any modification.

Poor (Low Quality)

Accuracy: Contains clear mistranslations, omissions, or semantic errors.

Factuality: Includes fabricated or irrelevant information not in the source.

Expression: Unnatural, awkward, or difficult to understand.

Usability: Not ready for use; requires revision.

Note:

If an *abbreviation* is widely recognized, publicly accepted, or commonly used in the industry (e.g., KFC, MBA), expanding it correctly in translation is considered good practice, not fabrication. If the *abbreviation* is less familiar, check its meaning online (e.g., DEI = Diversity, Equity, and Inclusion).

Original text: "A post in March 2024 accurately reported that Sylvester Stallone turned down \$100 million endorsement deal with beer brand Bud Light because he said it was too ""woke.""

Translation: 2024年3月的一篇帖子准确报道说, 西尔维斯特·史泰龙拒绝了一份与啤酒品牌百威淡啤的1亿美元代言合同, 因为他说这家公司“太觉醒”了。

Figure 7: Wrong example of Chinese translation from LLM

D Original language data

Due to the scarcity of open-source financial misinformation datasets, only a few English datasets specifically targeting financial misinformation have been identified. For other languages, we extract the financial portion from available open-source multidomain datasets.

D.1 English Part

FinDVer (Zhao et al., 2024): A benchmark for evaluating LLMs in claim verification over complex, financial-domain documents. It includes the Entailed Claim and the Refuted Claim. Entailed claims are generated by annotators through examining the textual and tabular information within each context, ensuring that the resulting statements naturally follow from the provided data and reflect realistic financial document comprehension. Refuted claims are produced by expert annotators through

Language	Dataset	Class	Number
English	FinDVer	Entailed	250
		Refuted	250
	GlobalEn	True	24
		False	121
Chinese	MDFEND	Real	250
		False	250
	CHEF	Supported	250
		NEI	250
	GlobalCh	True	24
		False	121
Bengali	BanMANI	MANI	52
		NO_MANI	49
	GlobalBe	True	24
		False	121
Greek	GlobalGr	True	24
		False	121

Table 4: MFMD Data Statistic. NEI: Not enough information.

perturbing the original entailed claims. The template is as follows. *[Claim]* is the claim to be verified. *[Document]* is the related financial report evidence.

Prompt template for FinDVer:

Task Description: Assess the truthfulness of the given statement by determining whether it is entailed or refuted based on the provided financial document. Output the entailment label ('entailed' or 'refuted') of the claim.

Claim: *[Claim]*

Relevant Financial Report: *[Document]*

D.2 Chinese Part

We collected the financial misinformation dataset from the multi-domain datasets MDFEND (Nan et al., 2021) and CHEF (Hu et al., 2022). MDFEND was collected from Weibo, which consists of 4,488 fake news and 4,640 real news from 9 different domains. CHEF is a Chinese evidence-based fact-checking dataset containing 10K real-world claims. It spans multiple domains, including politics, finance, and public health, and provides annotated evidence retrieved from the Internet. We filter the financial domain from the above datasets with the provided domain label. The templates for these two datasets are as follows:

Prompt template for MDFEND:

Task Description: Determine whether the following content is 'real' or 'false'.

Content: *[Content]*

Prompt template for CHEF:

Task Description: Label each claim based on the evidence provided. Choose one of the following three labels: Supported, which means there is sufficient evidence showing the claim is supported; Refuted, which means there is sufficient evidence showing the claim is refuted; Not enough information, which means the evidence is insufficient to determine whether the claim is supported or refuted.

Claim: [Claim]

Evidence: [Evidence]

D.3 Bengali Part

BanMANI (Kamruzzaman et al., 2023) collected 2.3k seed news articles from the BanFakeNews dataset (Hossain et al., 2020) across six domains where social media manipulation is most likely to occur: National, International, Politics, Entertainment, Crime, and Finance, while upsampling Politics and Entertainment following (Huang et al., 2025). These seed articles were used to generate both manipulated and non-manipulated social media content with ChatGPT, which was subsequently validated by human annotators. The template for BanMANI is as follows. [Original News] is the news from BanFakeNews, while [Social Media Post] is the social media content generated by ChatGPT.

Prompt template for BanMANI:

Task Description: Determine whether the social media post is manipulated or not manipulated based on the original news. Output 'MANI' in case the post is manipulated from the original news article, or output 'NO_MANI' otherwise.

Original News: [Original News]

Social Media Post: [Social Media Post]

For the datasets with large volumes, we sample 250 instances from each category for testing, so that the combined data with financial scenarios will not become excessively large. The statistics are shown in the Table 4.

D.4 Multilingual Evaluation

Table 5 presents the evaluation results on the MFMD dataset⁴. The results show that the large Qwen3 (14b, 32b) and GPT series maintain strong performance on Greek and Bengali, comparable to English and Chinese, thanks to their robust multilingual capabilities. In contrast, the LLaMA and Mistral series exhibit a noticeable performance gap between low-resource languages (Greek and Bengali) and high-resource languages (Chinese and

⁴Since Claude and Gemini refused to answer on most original language models, their results are not listed here.

English), indicating their relative weaknesses in low-resource settings.

When it comes to task complexity, the Mistral series performs relatively poorly on evidence-based misinformation detection tasks, highlighting its limitations in handling complex long-text tasks (i.e. FinDVer and CHEF). For models of the same size, The reasoning model do not significantly outperform the no-think model on financial misinformation detection tasks, as seen in the Qwen series, possibly because classification-based detection does not require extensive reasoning. Moreover, as observed in other tasks, model performance generally improves with increasing model size.

Overall, closed-source models, such as gpt-5-mini and GPT-4.1, still achieve the best results, suggesting that there remains a notable gap between open-source and closed-source models.

E Templates for evaluating LLMs

Template for base evaluation (i.e., no scenario)

Task Description: Determine whether the claim is 'True' or 'False'.

Claim: [claim]

Template for scenario evaluation

Task Description: Please take the scenario information into account. Determine whether the claim is 'True' or 'False'.

Scenario: [scenario]

Claim: [claim]

F Human performance on the GlobalEn dataset

To explore the differences between LLMs and real human performance in financial misinformation detection, we collected data from volunteers with investment experience across five regions on GlobalEn. The sample included 11 participants from China Mainland. Due to manpower constraints, only two participants were recruited from each of the Europe, Asia Pacific, Australia, and UAE regions. Volunteers were instructed to judge the truthfulness of claims solely based on their own past experiences and knowledge. The final human performance for each region was obtained by averaging the results within that region. Table 6 present the performance of 22 LLMs and Human. We observe that for the false category, Mistral-Large is relatively close to human performance in all scenarios except China Mainland, compared with other

Models	FinDVer		GlobalEn		MDFEND		CHEF		GlobalCh		MANI		GlobalBe		GlobalGr	
	ACC	F1	ACC	F1	ACC	F1	ACC	F1	ACC	F1	ACC	F1	ACC	F1	ACC	F1
Qwen3-8b-R	0.806	0.804	0.833	0.678	0.772	0.772	0.778	0.396	0.819	0.638	0.861	0.859	0.778	0.571	0.833	0.427
Qwen3-14b-R	0.826	0.551	0.861	0.710	0.736	0.725	0.788	0.533	0.861	0.667	0.851	0.848	0.840	0.673	0.833	0.619
Qwen3-32b-R	0.838	0.559	0.833	0.707	0.766	0.763	0.784	0.397	0.771	0.580	0.911	0.910	0.854	0.723	0.833	0.666
GPT-5-mini	0.830	0.554	0.868	0.758	0.748	0.736	0.774	0.526	0.854	0.701	0.941	0.940	0.889	0.777	0.896	0.802
Claude-Sonnet-4.5	-	-	0.847	0.725	-	-	-	-	0.882	0.532	-	-	0.861	0.765	0.882	0.791
Gemini-2.5	-	-	0.868	0.532	-	-	-	-	0.840	0.479	-	-	0.854	0.521	0.875	0.531
DeepSeek-Reasoner	-	-	0.861	0.498	-	-	-	-	0.903	0.551	-	-	0.903	0.836	0.889	0.793
Qwen3-8b	0.820	0.547	0.826	0.548	0.762	0.762	0.786	0.532	0.854	0.674	0.871	0.870	0.792	0.565	0.833	0.578
Qwen3-14b	0.822	0.821	0.813	0.657	0.714	0.702	0.796	0.537	0.806	0.624	0.842	0.838	0.785	0.385	0.840	0.606
Qwen3-32b	0.848	0.848	0.819	0.675	0.764	0.762	0.784	0.531	0.806	0.624	0.921	0.920	0.847	0.705	0.847	0.693
Qwen2.5-70b	0.702	0.507	0.875	0.759	0.816	0.815	0.506	0.303	0.840	0.726	0.386	0.365	0.847	0.693	0.847	0.693
Llama8b	0.742	0.496	0.792	0.476	0.594	0.449	0.562	0.286	0.549	0.366	0.485	0.258	0.188	0.120	0.542	0.339
Llama70b	0.712	0.507	0.882	0.797	0.790	0.533	0.312	0.291	0.729	0.654	0.267	0.275	0.306	0.302	0.813	0.534
Mistral-7b	0.238	0.216	0.833	0.406	0.658	0.452	0.056	0.052	0.847	0.398	0.059	0.072	0.764	0.296	0.792	0.369
Mistral-Large	0.248	0.257	0.778	0.492	0.532	0.422	0.086	0.101	0.785	0.471	0.069	0.085	0.681	0.421	0.729	0.450
Mistral-NEMO	0.298	0.262	0.847	0.705	0.508	0.294	0.082	0.097	0.868	0.718	0.208	0.151	0.847	0.500	0.868	0.636
Mistral-Small-24B	0.302	0.292	0.479	0.289	0.660	0.451	0.090	0.106	0.535	0.314	0.188	0.181	0.563	0.299	0.556	0.272
Mixtral-8x7B	0.202	0.202	0.667	0.413	0.486	0.347	0.064	0.059	0.486	0.294	0.040	0.043	0.479	0.307	0.410	0.288
Mixtral-8x22B	0.312	0.291	0.833	0.385	0.660	0.478	0.054	0.049	0.840	0.469	0.079	0.096	0.681	0.361	0.813	0.430
GPT-4.1	0.830	0.830	0.896	0.809	0.888	0.888	0.800	0.540	0.847	0.528	0.921	0.920	0.882	0.791	0.890	0.807
Claude-3.5-Haiku	-	-	0.875	0.528	-	-	-	-	0.840	0.519	-	-	0.722	0.341	0.792	0.367
Gemini-2.0-Flash	-	-	0.819	0.380	-	-	-	-	0.757	0.345	-	-	0.750	0.364	0.764	0.366
DeepSeek-Chat	-	-	0.854	0.428	-	-	-	-	0.840	0.659	-	-	0.840	0.584	0.882	0.724

Table 5: Evaluation results on the MFMD dataset.

Regions	Qwen3-8b-R	Qwen3-14b-R	Qwen3-32b-R	GPT-5-mini-R	Claude-4.5-R	Gemini-2.5-R	DeepSeek-R	Qwen8b	Qwen14b	Qwen2b	GPT-4.1	Claude-3.5	Gemini-2.0	DeepSeek-C	Qwen72b	Llama70b	Mistral-7B	Mistral-Large	Mistral-NEMO	Mistral-Small-24B	Mixtral-8x7B	Mixtral-8x22B	Human	Regions
Base	0.902	0.919	0.900	0.921	0.908	0.918	0.917	0.903	0.888	0.892	0.938	0.933	0.891	0.921	0.926	0.928	0.906	0.872	0.910	0.673	0.828	0.932	-	-
Europe	0.921	0.908	0.919	0.922	0.934	0.912	0.924	0.921	0.911	0.914	0.938	0.925	0.919	0.920	0.927	0.947	0.929	0.889	0.905	0.900	0.642	0.924	0.793	Europe
AsiaPacific	0.910	0.909	0.919	0.914	0.934	0.908	0.943	0.905	0.908	0.916	0.946	0.937	0.901	0.919	0.910	0.955	0.910	0.855	0.922	0.929	0.683	0.914	0.860	AsiaPacific
ChinaMainland	0.908	0.913	0.900	0.931	0.938	0.921	0.938	0.921	0.915	0.904	0.917	0.927	0.939	0.913	0.918	0.940	0.914	0.910	0.911	0.913	0.749	0.905	0.675	ChinaMainland
Australia	0.919	0.915	0.902	0.914	0.934	0.924	0.938	0.921	0.915	0.911	0.942	0.937	0.931	0.924	0.921	0.947	0.917	0.892	0.921	0.921	0.567	0.896	0.843	Australia
UAE	0.932	0.911	0.902	0.904	0.950	0.905	0.943	0.916	0.911	0.907	0.939	0.917	0.907	0.915	0.914	0.937	0.898	0.816	0.911	0.916	0.701	0.921	0.763	UAE
Base	0.455	0.500	0.500	0.596	0.542	0.679	0.578	0.194	0.426	0.458	0.681	0.651	0.627	0.364	0.591	0.667	0.313	0.605	0.500	0.194	0.412	0.222	-	-
Europe	0.411	0.143	0.500	0.578	0.652	0.571	0.640	0.411	0.206	0.512	0.667	0.550	0.537	0.153	0.571	0.711	0.437	0.594	0.333	0.303	0.266	0.414	0.525	Europe
AsiaPacific	0.303	0.000	0.524	0.533	0.636	0.560	0.666	0.333	0.076	0.433	0.723	0.622	0.445	0.275	0.500	0.731	0.312	0.473	0.375	0.437	0.439	0.297	0.351	AsiaPacific
ChinaMainland	0.378	0.080	0.324	0.604	0.681	0.612	0.681	0.411	0.214	0.369	0.565	0.513	0.652	0.000	0.545	0.615	0.275	0.545	0.258	0.363	0.285	0.215	0.418	ChinaMainland
Australia	0.523	0.267	0.429	0.533	0.652	0.640	0.681	0.444	0.266	0.450	0.696	0.572	0.605	0.230	0.596	0.697	0.375	0.457	0.444	0.387	0.222	0.414	0.479	Australia
UAE	0.540	0.207	0.429	0.530	0.750	0.510	0.682	0.432	0.206	0.439	0.651	0.550	0.439	0.214	0.533	0.555	0.235	0.473	0.258	0.363	0.205	0.357	0.377	UAE

Table 6: Human Evaluation on the GlobalEn dataset. Bold indicates the LLMs whose performance is closest to that of humans.

1325 models, while Mixtral-8x7B shows human-like per-
1326 formance in the China Mainland scenario. For the
1327 true category, the closest models vary by region:
1328 Gemini-2.0 in Europe, Qwen-8B in Asia regions,
1329 Mistral-Large in Australia, and Mistral-Small-24B
1330 in the UAE. Overall, current smaller-scale models
1331 tend to be closer to human performance, whereas
1332 larger models often exceed human performance.
1333 These results suggest that in misinformation detec-
1334 tion, small or medium-sized models are more likely
1335 to exhibit human-like behavior, while large models
1336 tend to display superhuman, systematically opti-
1337 mized behavior that differs from human judgment
1338 patterns.

1339 **G Results**

1340 **H Specific Cases (Tables 13 to 15)**

Role	Scenario	Qwen8B-R	Qwen14B-R	Qwen22B-R	GPT-5-mini-R	Claude-3.5-R	Gemini-1.5-R	DeepSeek-R	Qwen8B	Qwen14B	Qwen22B	GPT-4.1	GPPL-1	Claude-3.5	Gemini-2.0	DeepSeek-C	Qwen72b	Llama70b	Mistral-7B	Mistral-Large	Mistral-NEMO	Mistral-Small-2.0B	Mistral-8x7B	Mistral-8x22B	AM	MAV	
Implicit	Base	0.894	0.921	0.863	0.915	0.929	0.905	0.942	0.916	0.885	0.885	0.885	0.907	0.861	0.908	0.903	0.815	0.918	0.873	0.924	0.718	0.687	0.922	0.882	0.882	0.882	
	Overconfidence	0.027	-0.013	0.045	0.006	0.002	0.020	-0.003	-0.005	0.023	0.021	0.024	-0.012	0.053	0.001	0.019	0.109	0.002	0.056	-0.009	0.008	-0.034	-0.109	0.011	0.027	0.011	0.027
	LossAversion	0.028	-0.007	0.061	0.014	0.004	0.033	-0.003	-0.001	0.019	0.036	0.011	-0.013	0.070	0.021	0.006	0.096	0.001	0.042	-0.009	0.048	-0.065	-0.113	0.013	0.032	0.010	0.032
	Herding	0.019	-0.008	0.037	0.002	0.002	0.022	-0.007	-0.007	0.032	0.018	0.029	-0.007	0.064	0.001	0.030	0.106	-0.007	0.052	0.000	0.096	0.099	-0.112	0.021	0.034	0.010	0.034
	Anchoring	0.026	-0.008	0.040	0.014	-0.008	0.025	-0.020	-0.007	0.024	0.023	0.042	-0.040	0.067	0.009	0.032	0.107	-0.058	0.049	0.000	-0.004	-0.073	-0.111	0.006	0.036	0.010	0.036
	ConfirmationBias	0.030	-0.006	0.069	0.009	0.000	0.000	-0.021	0.005	0.003	0.039	0.028	-0.008	0.031	0.012	-0.004	0.104	-0.014	-0.007	0.011	0.000	-0.098	-0.085	0.003	0.027	0.010	0.027
	AM	0.026	-0.008	0.050	0.009	0.000	0.020	-0.011	-0.003	0.020	0.027	0.027	-0.016	0.057	0.009	0.017	0.104	-0.015	-0.006	0.030	-0.034	-0.106	0.011	0.029	0.010	0.029	
	MAV	0.026	-0.008	0.050	0.009	0.000	0.020	-0.011	-0.003	0.020	0.027	0.027	-0.016	0.057	0.009	0.017	0.104	-0.015	-0.006	0.030	-0.034	-0.106	0.011	0.029	0.010	0.029	
	Overconfidence	0.009	-0.013	0.050	0.017	0.010	0.028	0.005	-0.008	0.032	0.037	0.026	0.013	0.063	0.011	0.041	0.087	-0.007	0.048	-0.004	0.094	-0.031	-0.029	0.022	0.030	0.010	0.030
	LossAversion	0.021	-0.017	0.055	0.022	0.015	0.028	0.008	-0.005	0.019	0.052	0.024	0.010	0.065	-0.002	0.016	0.086	-0.005	0.029	0.003	0.123	0.081	-0.044	0.026	0.032	0.010	0.032
	Herding	0.006	-0.006	0.043	0.018	0.011	0.024	0.01	0.004	0.023	0.005	0.025	0.001	0.055	0.036	0.002	0.112	-0.010	0.043	0.003	0.051	-0.007	0.022	0.025	0.010	0.025	
	Anchoring	0.013	-0.017	0.054	0.018	0.000	0.003	0.001	-0.009	0.024	0.025	0.003	0.057	0.022	0.029	0.091	-0.001	0.043	0.000	0.145	0.104	-0.062	0.036	0.034	0.010	0.034	
	ConfirmationBias	0.006	-0.013	0.061	0.010	0.000	-0.012	-0.041	0.005	0.004	0.024	0.024	-0.002	0.044	0.000	-0.010	0.066	-0.012	0.012	-0.015	-0.013	0.010	-0.035	0.005	0.019	0.010	0.019
	AM	0.012	-0.013	0.053	0.016	0.010	0.018	-0.011	-0.005	0.018	0.021	0.022	-0.020	0.044	0.002	0.009	0.092	-0.008	0.036	-0.003	0.082	-0.071	-0.036	0.027	0.027	0.010	0.027
	MAV	0.012	-0.013	0.053	0.016	0.010	0.018	-0.011	-0.005	0.018	0.021	0.022	-0.020	0.044	0.002	0.009	0.092	-0.008	0.036	-0.003	0.082	-0.071	-0.036	0.027	0.027	0.010	0.027
Overconfidence	0.013	-0.013	0.051	0.014	0.026	0.024	-0.003	-0.001	0.020	0.018	0.012	0.013	0.053	0.003	0.011	0.104	-0.014	0.052	-0.004	0.101	0.111	-0.034	0.025	0.032	0.010	0.032	
LossAversion	0.021	-0.017	0.055	0.022	0.015	0.028	0.008	-0.005	0.019	0.052	0.024	0.010	0.065	-0.002	0.016	0.086	-0.005	0.029	0.003	0.123	0.081	-0.044	0.026	0.032	0.010	0.032	
Herding	0.006	-0.006	0.043	0.018	0.011	0.024	0.01	0.004	0.023	0.005	0.025	0.001	0.055	0.036	0.002	0.112	-0.010	0.043	0.003	0.051	-0.007	0.022	0.025	0.010	0.025		
Anchoring	0.013	-0.017	0.054	0.018	0.000	0.003	0.001	-0.009	0.024	0.025	0.003	0.057	0.022	0.029	0.091	-0.001	0.043	0.000	0.145	0.104	-0.062	0.036	0.034	0.010	0.034		
ConfirmationBias	0.006	-0.013	0.061	0.010	0.000	-0.012	-0.041	0.005	0.004	0.024	0.024	-0.002	0.044	0.000	-0.010	0.066	-0.012	0.012	-0.015	-0.013	0.010	-0.035	0.005	0.019	0.010	0.019	
AM	0.012	-0.013	0.053	0.016	0.010	0.018	-0.011	-0.005	0.018	0.021	0.022	-0.020	0.044	0.002	0.009	0.092	-0.008	0.036	-0.003	0.082	-0.071	-0.036	0.027	0.027	0.010	0.027	
MAV	0.012	-0.013	0.053	0.016	0.010	0.018	-0.011	-0.005	0.018	0.021	0.022	-0.020	0.044	0.002	0.009	0.092	-0.008	0.036	-0.003	0.082	-0.071	-0.036	0.027	0.027	0.010	0.027	
Overconfidence	0.013	-0.013	0.051	0.014	0.026	0.024	-0.003	-0.001	0.020	0.018	0.012	0.013	0.053	0.003	0.011	0.104	-0.014	0.052	-0.004	0.101	0.111	-0.034	0.025	0.032	0.010	0.032	
LossAversion	0.021	-0.017	0.055	0.022	0.015	0.028	0.008	-0.005	0.019	0.052	0.024	0.010	0.065	-0.002	0.016	0.086	-0.005	0.029	0.003	0.123	0.081	-0.044	0.026	0.032	0.010	0.032	
Herding	0.006	-0.006	0.043	0.018	0.011	0.024	0.01	0.004	0.023	0.005	0.025	0.001	0.055	0.036	0.002	0.112	-0.010	0.043	0.003	0.051	-0.007	0.022	0.025	0.010	0.025		
Anchoring	0.013	-0.017	0.054	0.018	0.000	0.003	0.001	-0.009	0.024	0.025	0.003	0.057	0.022	0.029	0.091	-0.001	0.043	0.000	0.145	0.104	-0.062	0.036	0.034	0.010	0.034		
ConfirmationBias	0.006	-0.013	0.061	0.010	0.000	-0.012	-0.041	0.005	0.004	0.024	0.024	-0.002	0.044	0.000	-0.010	0.066	-0.012	0.012	-0.015	-0.013	0.010	-0.035	0.005	0.019	0.010	0.019	
AM	0.012	-0.013	0.053	0.016	0.010	0.018	-0.011	-0.005	0.018	0.021	0.022	-0.020	0.044	0.002	0.009	0.092	-0.008	0.036	-0.003	0.082	-0.071	-0.036	0.027	0.027	0.010	0.027	
MAV	0.012	-0.013	0.053	0.016	0.010	0.018	-0.011	-0.005	0.018	0.021	0.022	-0.020	0.044	0.002	0.009	0.092	-0.008	0.036	-0.003	0.082	-0.071	-0.036	0.027	0.027	0.010	0.027	
Overconfidence	0.013	-0.013	0.051	0.014	0.026	0.024	-0.003	-0.001	0.020	0.018	0.012	0.013	0.053	0.003	0.011	0.104	-0.014	0.052	-0.004	0.101	0.111	-0.034	0.025	0.032	0.010	0.032	
LossAversion	0.021	-0.017	0.055	0.022	0.015	0.028	0.008	-0.005	0.019	0.052	0.024	0.010	0.065	-0.002	0.016	0.086	-0.005	0.029	0.003	0.123	0.081	-0.044	0.026	0.032	0.010	0.032	
Herding	0.006	-0.006	0.043	0.018	0.011	0.024	0.01	0.004	0.023	0.005	0.025	0.001	0.055	0.036	0.002	0.112	-0.010	0.043	0.003	0.051	-0.007	0.022	0.025	0.010	0.025		
Anchoring	0.013	-0.017	0.054	0.018	0.000	0.003	0.001	-0.009	0.024	0.025	0.003	0.057	0.022	0.029	0.091	-0.001	0.043	0.000	0.145	0.104	-0.062	0.036	0.034	0.010	0.034		
ConfirmationBias	0.006	-0.013	0.061	0.010	0.000	-0.012	-0.041	0.005	0.004	0.024	0.024	-0.002	0.044	0.000	-0.010	0.066	-0.012	0.012	-0.015	-0.013	0.010	-0.035	0.005	0.019	0.010	0.019	
AM	0.012	-0.013	0.053	0.016	0.010	0.018	-0.011	-0.005	0.018	0.021	0.022	-0.020	0.044	0.002	0.009	0.092	-0.008	0.036	-0.003	0.082	-0.071	-0.036	0.027	0.027	0.010	0.027	
MAV	0.012	-0.013	0.053	0.016	0.010	0.018	-0.011	-0.005	0.018	0.021	0.022	-0.020	0.044	0.002	0.009	0.092	-0.008	0.036	-0.003	0.082	-0.071	-0.036	0.027	0.027	0.010	0.027	
Overconfidence	0.013	-0.013	0.051	0.014	0.026	0.024	-0.003	-0.001	0.020	0.018	0.012	0.013	0.053	0.003	0.011	0.104	-0.014	0.052	-0.004	0.101	0.111	-0.034	0.025	0.032	0.010	0.032	
LossAversion	0.021	-0.017	0.055	0.022	0.015	0.028	0.008	-0.005	0.019	0.052	0.024	0.010	0.065	-0.002	0.016	0.086	-0.005	0.029	0.003	0.123	0.081	-0.044	0.026	0.032	0.010	0.032	
Herding	0.006	-0.006	0.043	0.018	0.011	0.024	0.01	0.004	0.023	0.005	0.025	0.001	0.055	0.036	0.002	0.112	-0.010	0.043	0.003	0.051	-0.007	0.022	0.025	0.010	0.025		
Anchoring	0.013	-0.017	0.054	0.018	0.000	0.003	0.001	-0.009	0.024	0.025	0.003	0.057	0.022	0.029	0.091	-0.001	0.043	0.000	0.145	0.104	-0.062	0.036	0.034	0.010	0.034		
ConfirmationBias	0.006	-0.013	0.061	0.010	0.000	-0.012	-0.041	0.005	0.004	0.024	0.024	-0.0															

Role	Scenario	Qwen8B-R	Qwen14B-R	Qwen22B-R	GPT-5-mini-R	Claude-3.5-R	Gemini-1.5-R	DeepSeek-R	Qwen8B	Qwen14B	Qwen22B	GPT-4.1	Claude-3.5	Gemini-2.0	DeepSeek-C	Qwen72b	Llama70b	Mistral-7B	Mistral-Large	Mistral-NEMO	Mistral-Small-2.1B	Mistral-8x7B	Mistral-8x22B	AM	MAV	
		FALSE Category																								
Implicit	Base	0.904	0.905	0.902	0.938	0.929	0.927	0.934	0.906	0.910	0.911	0.908	0.857	0.933	0.911	0.896	0.892	0.839	0.927	0.742	0.598	0.902	0.886	0.886		
	RetailInvestor	0.010	0.010	0.028	-0.010	0.010	-0.016	0.012	0.009	-0.001	0.019	0.009	-0.028	0.069	-0.011	0.009	0.018	-0.206	-0.039	-0.015	0.026	0.072	-0.067	-0.004	0.031	
	LossAversion	-0.001	0.011	0.006	0.006	-0.008	-0.017	-0.014	0.005	0.003	0.005	0.017	-0.006	0.070	0.008	0.004	0.008	-0.147	-0.019	0.073	-0.020	-0.066	-0.009	-0.009	0.029	
	Herding	0.001	0.008	0.017	-0.001	-0.005	-0.004	0.001	0.007	-0.001	0.004	0.014	-0.040	0.077	-0.010	0.018	0.013	-0.191	0.028	-0.014	0.101	0.225	-0.095	0.007	0.040	
	Anchoring	0.004	0.004	0.007	-0.003	0.004	-0.010	-0.005	0.003	0.003	-0.002	0.009	-0.157	0.063	-0.009	0.017	0.037	-0.147	0.025	-0.014	-0.075	0.069	-0.052	-0.009	0.030	
	ConfirmationBias	0.012	-0.006	0.014	-0.008	-0.007	-0.035	-0.007	0.013	0.003	0.009	0.013	-0.044	0.026	-0.008	0.019	0.007	-0.115	-0.048	-0.023	-0.022	0.005	-0.019	-0.017	0.027	
	AM	0.005	0.006	0.014	-0.003	-0.001	-0.016	-0.003	0.007	0.001	0.007	0.012	-0.075	0.061	-0.006	0.013	0.017	-0.161	-0.011	-0.017	0.037	0.075	-0.089	-0.006	0.029	
	MAV	0.006	0.008	0.014	0.006	0.007	0.016	0.008	0.007	0.002	0.008	0.012	0.075	0.061	0.009	0.013	0.017	0.161	0.032	0.017	0.046	0.083	0.089	0.032	0.032	
	Professional	Overconfidence	0.003	0.004	0.023	-0.032	0.004	-0.020	-0.019	0.007	-0.001	0.007	0.014	-0.071	0.074	-0.006	0.009	0.028	-0.141	0.022	-0.019	0.077	0.131	-0.046	0.002	0.034
	LossAversion	0.004	0.006	0.031	-0.006	0.018	-0.008	-0.005	0.012	-0.002	0.014	0.005	-0.073	0.085	-0.007	0.020	0.042	-0.158	-0.075	-0.014	0.049	0.168	-0.047	0.003	0.039	
Herding	0.023	0.004	0.021	-0.005	0.016	-0.018	-0.004	0.003	-0.001	0.005	0.018	-0.042	0.074	-0.006	0.029	0.020	-0.137	-0.003	-0.014	0.105	0.204	-0.084	0.003	0.038		
Anchoring	-0.008	0.010	0.027	0.001	-0.009	-0.008	0.002	0.013	0.002	0.021	0.017	-0.117	0.080	0.004	0.013	0.016	-0.055	-0.054	-0.015	0.097	-0.101	-0.098	-0.007	0.035		
ConfirmationBias	0.009	0.003	0.018	0.001	-0.003	-0.013	-0.006	0.014	0.003	0.022	-0.004	-0.072	0.076	0.003	0.006	0.001	-0.083	-0.107	-0.014	-0.075	0.069	-0.052	-0.009	0.030		
AM	0.006	0.002	0.024	-0.008	0.005	-0.013	-0.006	0.010	0.000	0.014	0.010	-0.075	0.078	-0.002	0.015	0.021	-0.115	-0.043	-0.013	0.031	0.094	-0.066	-0.001	0.031		
MAV	0.009	0.005	0.024	0.009	0.010	0.013	0.007	0.010	0.002	0.014	0.011	0.075	0.078	0.005	0.015	0.021	0.115	0.052	0.015	0.081	0.134	0.066	0.035	0.035		
CompanyOwner	Overconfidence	0.010	0.015	0.013	-0.002	-0.002	-0.017	-0.012	0.010	-0.005	0.008	0.017	-0.044	0.061	-0.015	-0.004	0.002	-0.089	-0.054	-0.014	0.079	0.091	-0.044	0.000	0.028	
LossAversion	0.011	0.003	0.007	0.006	-0.008	-0.016	-0.023	0.009	-0.001	0.011	0.005	-0.124	0.069	-0.003	-0.005	0.012	-0.078	-0.063	-0.019	0.085	0.154	-0.021	0.001	0.033		
Herding	0.003	0.000	0.015	-0.002	0.033	-0.012	-0.007	0.010	-0.002	0.010	0.017	-0.047	0.063	-0.006	0.012	-0.012	-0.133	0.020	-0.010	0.060	0.164	-0.074	0.003	0.032		
Anchoring	0.003	0.011	0.028	-0.015	0.001	-0.015	0.007	0.009	-0.001	0.007	0.013	-0.091	0.051	-0.009	0.017	0.019	-0.029	-0.043	-0.014	0.119	0.178	-0.095	0.007	0.035		
ConfirmationBias	-0.031	-0.006	-0.009	-0.003	0.005	-0.005	-0.021	0.004	0.002	-0.008	0.005	-0.076	0.067	-0.003	0.011	-0.010	-0.013	-0.067	-0.015	-0.009	0.019	-0.098	-0.012	0.022		
AM	-0.001	0.004	0.011	-0.003	0.005	-0.013	-0.011	0.009	-0.001	0.006	0.012	-0.076	0.062	-0.007	0.006	0.002	-0.068	-0.049	-0.015	0.067	0.121	-0.066	0.000	0.028		
MAV	0.011	0.007	0.014	0.005	0.010	0.014	0.009	0.005	0.009	0.012	0.006	0.012	0.062	0.007	0.010	0.011	0.068	0.044	0.015	0.071	0.161	0.066	0.030	0.030		
Explicit	Base	0.904	0.905	0.902	0.938	0.929	0.927	0.934	0.906	0.910	0.911	0.933	0.904	0.857	0.933	0.911	0.896	0.892	0.839	0.927	0.742	0.598	0.902	0.886	0.886	
	RetailInvestor	0.009	-0.005	0.025	-0.012	-0.013	-0.142	-0.010	0.005	0.003	0.017	-0.005	-0.026	0.037	-0.012	0.012	0.012	-0.219	-0.059	-0.019	-0.001	0.099	-0.104	-0.019	0.038	
	LossAversion	0.002	0.002	0.009	-0.007	0.006	-0.002	-0.012	0.023	-0.002	0.010	-0.009	-0.078	0.079	0.004	0.016	0.022	-0.121	-0.039	-0.019	-0.040	0.028	-0.069	-0.009	0.027	
	Herding	0.019	0.003	0.022	0.010	0.010	-0.009	0.004	0.014	-0.001	0.018	0.005	-0.052	0.069	0.001	0.026	-0.005	-0.175	-0.030	-0.014	-0.020	0.202	-0.066	0.001	0.034	
	Anchoring	0.014	-0.001	0.016	-0.010	-0.002	0.006	-0.001	0.003	0.003	0.000	0.009	-0.053	0.045	0.001	-0.003	0.020	-0.134	-0.014	-0.014	0.038	0.030	-0.091	-0.006	0.023	
	ConfirmationBias	0.013	-0.002	0.019	-0.007	-0.012	-0.020	0.007	0.010	0.003	0.014	0.012	0.007	0.076	-0.003	0.003	0.006	-0.127	-0.013	-0.014	0.060	0.037	-0.054	0.001	0.024	
	AM	0.012	0.001	0.018	-0.005	-0.002	-0.033	-0.002	0.011	0.001	0.012	0.003	-0.040	0.061	-0.002	0.011	0.011	-0.155	-0.031	-0.016	0.007	0.079	-0.077	-0.006	0.027	
	MAV	0.012	0.005	0.016	0.008	0.007	0.007	0.015	0.002	0.012	0.011	0.078	0.081	0.008	0.019	0.017	0.068	0.099	-0.015	0.031	0.042	0.063	0.021	0.021	0.021	
	Professional	Overconfidence	0.009	0.011	0.007	-0.003	0.010	0.004	-0.006	0.016	-0.001	0.013	0.001	-0.126	0.093	-0.002	0.021	0.035	-0.141	-0.084	-0.019	0.006	0.044	-0.055	-0.008	0.032
	LossAversion	0.014	0.005	-0.002	-0.016	-0.005	0.000	0.002	0.007	0.006	0.014	0.005	-0.055	0.072	0.015	0.011	-0.008	-0.050	-0.014	-0.021	-0.023	-0.088	-0.013	0.027	0.027	
Herding	0.010	0.010	0.016	-0.014	0.012	-0.008	-0.028	0.010	-0.001	0.018	0.009	-0.052	0.082	-0.009	0.025	0.026	-0.143	-0.054	-0.014	0.051	0.141	-0.081	0.000	0.037		
Anchoring	0.006	0.006	0.008	0.006	-0.004	-0.001	-0.001	0.004	-0.001	0.004	0.005	-0.076	0.067	-0.003	0.003	0.001	-0.083	-0.014	-0.004	0.034	0.034	-0.062	-0.010	0.026		
ConfirmationBias	0.021	-0.001	0.023	-0.003	-0.008	-0.019	-0.034	0.028	0.003	0.013	0.017	-0.083	0.071	0.001	0.006	0.014	-0.075	-0.111	-0.014	-0.072	0.036	-0.064	0.012	0.032		
AM	0.012	0.009	0.015	-0.006	0.002	-0.004	-0.016	0.015	0.002	0.012	0.011	-0.078	0.081	-0.001	0.019	0.013	-0.088	-0.099	-0.015	0.088	0.042	-0.063	-0.007	0.028		
MAV	0.012	0.010	0.016	0.008	0.007	0.007	0.015	0.002	0.012	0.011	0.078	0.081	0.008	0.019	0.017	0.068	0.099	-0.015	0.031	0.042	0.063	0.021	0.021	0.021		
CompanyOwner	Overconfidence	0.008	0.003	0.016	0.006	0.008	-0.017	-0.015	0.002	-0.001	0.003	0.001	-0.098	0.070	-0.021	0.000	0.003	-0.041	-0.048	-0.014	0.115	0.107	-0.075	0.001	0.031	
LossAversion	0.011	0.003	0.022	0.002	0.022	-0.017	-0.006	0.006	0.003	-0.005	-0.001	-0.059	0.051	-0.013	0.000	0.022	-0.119	-0.048	-0.010	0.034	0.163	-0.081	-0.004	0.032		
Herding	0.006	0.003	0.018	0.002	0.000	-0.016	0.003	0.010	0.003	0.003	0.009	-0.061	0.070	0.009	0.016	0.017	-0.068	-0.061	-0.010	0.112	0.150	-0.066	0.006	0.032		
Anchoring	0.007	0.014	-0.009	0.002	0.005	-0.031	-0.020	-0.008	0.002	-0.023	0.005	-0.076	0.067	-0.003	0.001	-0.005	-0.019	-0.078	-0.019	-0.042	0.079	-0.082	-0.010	0.026		
ConfirmationBias	0.006	0.006	0.011	0.000	-0.010	-0.019	-0.010	0.005	0.001	-0.007	0.003	-0.057	0.064	-0.007	0.004	0.010	-0.081	-0.017	-0.013	0.053	0.115	-0.070	-0.002	0.028		
AM	0.007	0.006	0.014	0.005	0.010	0.019	0.011	0.008	0.002	0.008	0.005	0.057	0.064	0.010	0.004	0.012	0.081	0.071	0.013	0.084	0.115	0.070	0.031	0.031		
Implicit	Base	0.378	0.333	0.429	0.667	0.653	0.667	0.652	0.250	0.303	0.476	0.680	0.564	0.609	0.514	0.476	0.706	0.214	0.512	0.345	0.074	0.267	0.387	0.462	0.462	
	RetailInvestor	-0.066	-0.119	0.009	-0.141	-0.002	-0.079	0.071	0.026	-0.303	-0.039	0.028	-0.008	-0.031	-0.181	-0.002	-0.244	-0.214	-0.012	-0.197	-0.074	-0.267	-0.233	-0.094	0.107	
	LossAversion	-0.184	-0.179	-0.019	-0.017	-0.057	-0.049	-0.025	-0.043	-0.223	-0.014	0.080	-0.120	-0.177	0.031	0.012	-0.161	-0.131	-0.055	-0.268	-0.074	-0.023	-0.239	-0.090	0.101	
	Herding	-0.378	-0.333	-0.153	-0.111	-0.422	-0.130	-0.033	-0.170	-0.303	-0.209	0.018	-0.079	-0.313	-0.228	-0.005	-0.342	-0.214	-0.29							

Role	Scenario	Qwen8B-R	Qwen7B-R	Qwen7B-R	GPT-5-mini-R	Claude-3.5-R	Gemini-2.5-R	DeepSeek-R	Qwen8B	Qwen7B	Qwen7B	GPT-4.1	Claude-3.5	Gemini-2.0	DeepSeek-C	Qwen7B	Llama7B	Mistral-7B	Mistral-Large	Mistral-NEMO	Mistral-Small-2.0B	Mistral-8B-7B	Mistral-8B-22B	AM	MAV
		FALSE Category																							
Implicit	Base	0.869	0.907	0.914	0.935	0.915	0.909	0.941	0.879	0.877	0.910	0.929	0.866	0.845	0.911	0.911	0.446	0.887	0.813	0.917	0.738	0.670	0.825	0.855	0.855
RetailInvestor	Overconfidence	0.045	0.009	0.007	-0.008	0.004	0.012	-0.021	0.036	0.052	0.012	0.014	-0.060	0.072	0.016	0.009	0.015	-0.166	0.025	-0.004	0.055	-0.013	-0.042	0.002	0.031
	LossAversion	0.021	0.009	-0.034	0.000	0.019	0.028	-0.004	0.015	0.039	-0.009	0.017	-0.190	0.080	0.019	0.009	0.080	0.028	0.000	0.087	0.043	-0.142	-0.002	0.040	0.040
	Herding	0.044	0.002	-0.014	-0.024	-0.007	0.002	-0.015	0.034	0.032	-0.009	0.002	-0.142	0.077	0.012	0.014	0.054	-0.167	0.020	-0.004	0.079	0.166	-0.119	0.002	0.047
	Anchoring	0.047	0.006	0.004	-0.012	0.012	-0.006	-0.020	0.034	0.036	0.010	0.002	-0.377	0.057	0.013	0.005	0.165	-0.075	0.045	-0.004	0.075	0.030	-0.162	0.054	0.047
	ConfirmationBias	0.044	0.000	0.000	-0.016	0.012	-0.003	-0.025	0.035	0.043	-0.007	0.008	-0.154	0.062	0.021	0.023	-0.009	-0.085	-0.092	-0.013	-0.089	-0.138	-0.073	-0.021	0.043
	AM	0.040	0.005	-0.007	-0.012	0.008	0.006	-0.017	0.031	0.036	-0.001	0.008	-0.185	0.069	0.016	0.014	0.045	-0.115	0.005	-0.005	0.041	0.017	-0.107	-0.005	0.036
	MAV	0.040	0.005	0.012	0.012	0.017	0.010	0.017	0.021	0.036	0.009	0.008	-0.185	0.069	0.016	0.014	0.045	-0.115	0.005	-0.005	0.041	0.017	-0.107	-0.043	0.043
Professional	Overconfidence	0.043	0.009	0.004	-0.003	0.002	-0.001	-0.007	0.045	0.032	0.005	0.014	-0.246	0.073	0.020	0.016	0.039	-0.145	0.033	-0.004	0.108	0.094	-0.165	-0.002	0.050
	LossAversion	0.040	-0.004	0.019	0.001	0.000	0.024	-0.034	0.028	0.043	0.011	0.018	-0.208	0.071	0.022	0.018	-0.046	-0.130	-0.164	-0.004	0.083	0.071	-0.067	-0.016	0.050
	Herding	0.035	0.017	0.008	-0.010	0.019	0.000	-0.017	0.038	0.036	0.007	-0.002	-0.140	0.079	0.013	0.008	0.026	-0.126	-0.052	-0.004	0.131	0.114	-0.234	-0.002	0.051
	Anchoring	0.031	0.005	0.003	-0.003	0.002	0.013	-0.009	0.020	0.039	-0.002	0.012	-0.247	0.088	0.014	0.008	-0.102	-0.037	-0.079	-0.009	0.078	-0.080	-0.158	-0.019	0.047
	ConfirmationBias	0.044	0.009	0.000	-0.019	0.028	0.009	-0.025	0.055	0.043	0.003	0.005	-0.180	0.088	0.013	0.002	-0.006	-0.070	-0.170	-0.009	0.002	-0.138	-0.009	-0.075	0.043
	AM	0.039	0.007	0.007	-0.007	0.010	0.009	-0.020	0.037	0.038	0.003	0.009	-0.262	0.080	0.016	0.010	-0.018	-0.092	-0.096	-0.096	0.081	0.076	-0.125	-0.011	0.042
	MAV	0.039	0.009	0.007	0.007	0.010	0.009	0.020	0.037	0.038	0.006	0.010	0.204	0.080	0.016	0.010	0.044	0.102	0.099	0.006	0.081	0.100	0.126	0.048	0.048
CompanyOwner	Overconfidence	0.042	0.006	-0.002	-0.016	0.009	-0.003	-0.004	0.029	0.032	0.002	0.021	-0.119	0.076	0.027	0.013	0.051	-0.127	-0.006	-0.004	0.090	0.156	-0.086	0.008	0.042
	LossAversion	0.037	0.006	0.008	0.005	0.003	0.015	-0.038	0.033	0.043	0.020	0.000	-0.159	0.076	0.016	0.003	-0.030	0.000	-0.009	0.102	0.163	-0.014	0.010	0.038	
	Herding	0.034	0.006	-0.004	0.008	0.015	-0.006	-0.016	0.025	0.039	-0.008	0.013	-0.230	0.072	0.020	0.001	0.035	-0.147	-0.009	-0.004	0.044	0.087	-0.061	-0.040	0.040
	Anchoring	0.034	0.006	-0.007	-0.015	0.009	0.006	-0.006	0.025	0.035	0.005	0.018	-0.109	0.077	0.008	0.021	0.135	-0.028	0.004	0.123	0.147	-0.045	0.021	0.041	
	ConfirmationBias	0.020	0.000	0.009	-0.003	-0.006	-0.009	-0.021	0.019	0.031	0.001	0.012	-0.197	0.055	-0.013	0.001	0.014	-0.054	-0.030	-0.005	0.040	-0.100	-0.090	-0.015	0.033
	AM	0.023	0.004	0.001	-0.004	0.006	0.000	-0.017	0.026	0.036	0.003	0.013	-0.163	0.071	0.011	0.008	0.041	-0.081	-0.002	-0.005	0.080	-0.089	-0.059	0.004	0.034
	MAV	0.023	0.004	0.006	0.009	0.008	0.008	0.017	0.026	0.036	0.007	0.013	-0.163	0.071	0.011	0.008	0.041	-0.081	-0.002	-0.005	0.080	-0.089	-0.059	0.039	0.039
Explicit	Base	0.869	0.907	0.914	0.935	0.915	0.909	0.941	0.879	0.877	0.910	0.929	0.866	0.845	0.911	0.911	0.446	0.887	0.813	0.917	0.738	0.670	0.825	0.855	0.855
RetailInvestor	Overconfidence	0.041	0.005	-0.003	-0.006	-0.006	-0.132	-0.013	0.040	0.026	0.014	0.013	-0.060	0.063	0.014	0.003	0.051	-0.214	-0.022	-0.008	0.035	-0.110	-0.112	-0.013	0.041
	LossAversion	0.023	0.004	-0.001	-0.024	-0.018	0.005	-0.025	0.013	0.028	0.007	0.008	-0.098	0.067	0.030	0.003	0.063	-0.057	-0.015	-0.004	-0.023	0.010	-0.187	-0.009	0.022
	Herding	0.011	0.001	0.004	0.010	0.012	-0.012	0.029	0.032	0.016	0.011	0.009	-0.078	0.023	0.013	0.005	0.075	-0.173	-0.009	-0.005	0.013	-0.002	-0.044	-0.004	0.033
	Anchoring	0.034	0.006	-0.001	0.001	-0.007	-0.002	-0.016	0.026	0.036	0.006	-0.002	-0.169	0.056	0.023	-0.010	-0.023	-0.110	-0.058	0.004	0.023	-0.057	-0.175	-0.019	0.038
	ConfirmationBias	0.041	0.006	0.015	-0.018	-0.001	0.024	-0.008	0.033	0.039	0.008	0.025	0.001	0.068	0.019	0.023	-0.006	-0.159	-0.083	0.000	0.044	-0.069	-0.110	-0.005	0.036
	AM	0.030	0.004	0.002	-0.010	-0.004	-0.019	-0.015	0.028	0.032	0.010	0.011	-0.081	0.069	0.020	0.005	0.032	-0.142	-0.050	-0.005	0.003	-0.023	-0.117	-0.010	0.032
	MAV	0.030	0.004	0.002	-0.010	-0.004	-0.019	-0.015	0.028	0.032	0.010	0.011	-0.081	0.069	0.020	0.005	0.032	-0.142	-0.050	-0.005	0.003	-0.023	-0.117	-0.010	0.032
Professional	Overconfidence	0.039	0.005	0.005	-0.026	-0.004	0.005	-0.030	0.028	0.031	0.007	0.017	-0.316	0.066	0.023	0.004	-0.069	-0.108	-0.054	-0.004	0.109	-0.053	-0.169	-0.022	0.053
	LossAversion	0.025	0.005	0.003	0.005	0.023	0.014	-0.045	0.032	0.033	0.011	0.009	-0.180	0.079	0.021	0.002	-0.031	-0.063	-0.088	-0.009	0.007	-0.127	-0.065	-0.015	0.040
	Herding	0.030	0.009	0.001	0.002	-0.002	-0.001	-0.024	0.026	0.035	0.008	0.021	-0.226	0.061	0.020	0.011	-0.078	-0.143	-0.083	-0.004	0.076	0.112	-0.057	-0.009	0.047
	Anchoring	0.030	0.009	0.001	0.002	-0.002	-0.001	-0.024	0.026	0.035	0.008	0.021	-0.226	0.061	0.020	0.011	-0.078	-0.143	-0.083	-0.004	0.076	0.112	-0.057	-0.009	0.047
	ConfirmationBias	0.036	0.005	-0.005	-0.048	0.016	0.001	-0.045	0.021	0.039	-0.013	0.025	-0.281	0.087	0.031	0.001	-0.003	-0.036	-0.077	-0.067	0.000	-0.062	-0.058	-0.023	0.047
	AM	0.032	0.005	-0.004	-0.014	0.010	-0.002	-0.032	0.023	0.034	0.005	0.014	-0.260	0.073	0.024	0.004	-0.074	-0.083	-0.069	-0.005	0.031	-0.044	-0.091	-0.019	0.043
	MAV	0.032	0.005	0.007	0.017	0.013	0.009	0.032	0.023	0.034	0.010	0.015	-0.260	0.073	0.024	0.005	0.074	-0.083	-0.069	-0.005	0.031	-0.044	-0.091	-0.019	0.043
CompanyOwner	Overconfidence	0.042	0.009	-0.005	-0.003	0.005	0.002	-0.009	0.016	0.025	0.012	0.009	-0.156	0.063	0.000	-0.018	0.011	-0.211	-0.039	-0.004	0.116	-0.059	0.027	-0.007	0.039
	LossAversion	0.027	0.006	0.007	-0.003	0.001	0.020	-0.013	0.034	0.032	0.008	0.009	-0.187	0.052	0.016	0.001	0.048	-0.070	0.003	-0.004	0.120	0.110	-0.023	0.009	0.036
	Herding	0.042	0.002	0.007	-0.015	0.021	-0.008	-0.037	0.032	0.039	0.008	0.008	-0.113	0.071	0.011	0.010	0.054	-0.114	-0.039	-0.004	0.025	-0.007	-0.128	-0.011	0.036
	Anchoring	0.042	0.002	0.016	0.005	0.023	0.012	0.013	0.029	0.032	0.008	0.010	-0.072	0.081	0.034	-0.003	0.023	-0.069	-0.015	-0.004	0.106	0.089	-0.081	0.014	0.025
	ConfirmationBias	0.041	0.004	-0.006	-0.013	0.015	0.001	-0.044	0.009	0.038	-0.010	0.005	-0.115	0.052	0.014	0.005	0.042	-0.052	-0.028	-0.009	0.054	0.199	-0.061	-0.013	0.036
	AM	0.039	0.005	0.004	-0.006	0.017	0.005	-0.018	0.024	0.032	0.005	0.006	-0.128	0.064	0.015	0.008	0.014	-0.103	-0.018	-0.005	0.080	-0.013	-0.002	-0.002	0.030
	MAV	0.039	0.005	0.008	0.008	0.013	0.008	0.023	0.024	0.035	0.009	0.008	-0.128	0.064	0.015	0.008	0.035	0.103	0.025	0.080	0.093	0.064	0.036	0.036	0.036
		TRUE Category																							
Implicit	Base	0.273	0.439	0.533	0.619	0.615	0.655	0.731	0.250	0.279	0.500	0.628	0												

Role	Scenario	FALSE Category																				AM	MAV		
		Qwen3b-R	Qwen1.8b-R	Qwen3.2b-R	GPT-5.5mini-R	Claude-4.5-R	Gemini2.5-R	DeepSeek-R	Qwen3b	Qwen1.8b	Qwen3.2b	GPT-4.1	Claude-3.5	Gemini2.0	DeepSeek-C	Qwen7.2b	Llama7.7b	Mistral7B	MistralLarge	MistralNEMO	MistralSmall24B			Mistral8.7B	Mistral8.22B
RetailInvestor	Base	0.902	0.919	0.900	0.921	0.908	0.918	0.917	0.903	0.888	0.892	0.938	0.933	0.891	0.921	0.926	0.928	0.906	0.872	0.910	0.673	0.828	0.932	0.897	0.897
	Europe	0.019	-0.011	0.019	0.001	0.026	-0.006	0.007	0.018	0.023	0.022	0.000	-0.008	0.028	-0.001	0.001	0.019	0.023	0.017	-0.005	0.227	-0.186	-0.008	0.010	0.031
	USA	0.022	0.003	-0.017	0.005	0.030	-0.007	0.007	0.032	0.020	0.020	0.016	-0.009	0.054	0.013	-0.013	0.013	-0.004	0.044	0.012	0.251	-0.175	0.009	0.015	0.035
	AsiaPacific	0.018	-0.010	0.019	-0.007	0.026	0.010	0.026	0.002	0.020	0.024	0.008	0.004	0.010	0.002	-0.016	0.027	0.004	-0.017	0.012	0.256	-0.145	-0.018	0.010	0.031
	ChinaMainland	0.006	-0.006	0.000	0.010	0.030	0.003	0.021	0.018	0.027	0.012	-0.021	-0.006	0.048	-0.008	-0.008	0.012	0.008	0.038	0.001	0.240	-0.079	-0.027	0.010	0.029
	Australia	0.017	-0.004	0.002	-0.007	0.026	0.006	0.021	0.018	0.027	0.019	0.004	0.004	0.040	0.003	-0.005	0.019	0.011	0.020	0.011	0.248	-0.261	-0.036	0.008	0.037
	UAE	0.030	-0.008	0.002	-0.017	0.042	-0.013	0.026	0.013	0.023	0.015	0.001	-0.016	0.016	-0.006	-0.012	0.009	-0.008	-0.056	0.001	0.243	-0.127	-0.011	0.007	0.032
	AM	0.017	0.007	0.010	0.008	0.030	0.007	0.018	0.017	0.024	0.020	0.008	0.008	0.032	0.005	0.009	0.016	0.009	0.032	0.007	0.244	-0.162	-0.018	0.032	0.031
	MAV	0.008	-0.008	0.002	0.007	0.026	0.003	0.002	0.005	0.024	0.031	0.003	-0.007	0.033	0.009	-0.007	0.012	0.000	-0.021	0.002	0.228	-0.092	-0.033	0.021	0.026
	MAV	0.010	0.005	0.005	0.026	0.009	0.005	0.014	0.024	0.021	0.024	0.007	0.033	0.011	0.007	0.012	0.011	0.042	0.044	0.228	0.028	0.028	0.028	0.028	0.028
Professional	Base	0.014	-0.019	0.002	0.005	0.033	-0.021	0.003	0.005	0.016	0.027	0.021	0.000	0.036	-0.002	0.005	0.015	0.023	0.030	0.003	0.240	-0.131	-0.026	0.012	0.031
	Europe	0.002	0.001	0.014	0.005	0.025	0.000	0.002	0.013	0.028	0.013	0.004	0.000	0.043	0.028	-0.002	0.022	0.010	0.002	0.006	0.240	-0.024	-0.006	0.020	0.023
	USA	0.001	-0.015	-0.002	0.001	0.039	0.007	-0.006	-0.012	0.028	0.043	0.000	0.017	0.026	0.013	-0.009	0.005	0.001	-0.051	0.002	0.185	-0.028	-0.024	0.010	0.023
	AsiaPacific	0.006	-0.003	0.002	0.018	0.025	0.014	0.013	0.006	0.024	0.027	-0.004	-0.007	0.020	-0.004	-0.004	0.004	0.009	-0.010	-0.004	0.246	-0.186	-0.048	0.007	0.031
	ChinaMainland	0.030	-0.004	0.008	0.000	0.016	0.014	0.003	0.024	0.020	0.027	0.000	-0.012	0.034	0.006	-0.017	0.002	0.015	0.032	0.006	0.236	-0.100	-0.064	0.013	0.030
	Australia	0.007	-0.008	0.002	0.010	0.021	0.001	-0.006	-0.008	0.027	0.030	0.000	-0.006	0.039	0.012	-0.004	0.027	0.000	-0.129	0.001	0.221	-0.085	-0.030	0.004	0.031
	UAE	0.008	-0.008	0.002	0.010	0.021	0.001	-0.006	-0.008	0.027	0.030	0.000	-0.006	0.039	0.012	-0.004	0.027	0.000	-0.129	0.001	0.221	-0.085	-0.030	0.004	0.031
	AM	0.008	-0.008	0.002	0.010	0.021	0.001	-0.006	-0.008	0.027	0.030	0.000	-0.006	0.039	0.012	-0.004	0.027	0.000	-0.129	0.001	0.221	-0.085	-0.030	0.004	0.031
	MAV	0.008	-0.008	0.002	0.010	0.021	0.001	-0.006	-0.008	0.027	0.030	0.000	-0.006	0.039	0.012	-0.004	0.027	0.000	-0.129	0.001	0.221	-0.085	-0.030	0.004	0.031
	MAV	0.008	-0.008	0.002	0.010	0.021	0.001	-0.006	-0.008	0.027	0.030	0.000	-0.006	0.039	0.012	-0.004	0.027	0.000	-0.129	0.001	0.221	-0.085	-0.030	0.004	0.031
CompanyOwner	Base	0.009	0.000	0.005	0.019	0.030	0.014	-0.006	-0.001	0.023	-0.005	-0.004	-0.011	0.028	0.002	-0.035	0.006	-0.006	-0.049	0.008	0.235	-0.060	-0.003	0.009	0.025
	Europe	-0.012	-0.004	0.007	-0.010	0.026	-0.010	0.008	-0.008	0.023	0.005	-0.009	-0.004	0.030	0.021	-0.033	-0.018	0.005	0.036	0.003	0.248	-0.008	-0.006	0.014	0.024
	USA	0.006	-0.014	0.022	0.004	0.021	0.003	0.025	0.004	0.017	0.030	-0.018	0.005	0.030	0.013	-0.018	-0.001	0.001	0.012	-0.002	0.254	-0.105	-0.047	0.011	0.030
	AsiaPacific	-0.015	-0.009	0.019	-0.017	0.034	-0.019	0.009	0.139	-0.249	0.026	0.042	-0.029	-0.183	-0.008	-0.091	0.065	-0.001	-0.131	-0.123	0.244	-0.077	0.074	-0.019	0.102
	ChinaMainland	0.077	-0.420	-0.176	0.009	0.139	-0.067	0.103	0.218	-0.212	-0.090	-0.116	-0.138	0.024	-0.364	-0.046	-0.052	-0.037	-0.060	-0.242	0.170	-0.126	-0.008	-0.077	0.131
	Australia	0.069	-0.223	-0.071	-0.063	0.110	-0.039	0.103	0.250	-0.159	-0.008	0.015	-0.080	-0.022	-0.133	0.005	0.031	0.062	-0.148	-0.056	0.193	-0.190	0.192	-0.008	0.101
	UAE	0.086	-0.293	-0.071	-0.065	0.208	-0.168	0.104	0.238	-0.219	-0.109	-0.030	-0.101	-0.188	-0.150	-0.058	-0.111	-0.078	-0.131	-0.242	0.170	-0.207	0.135	-0.054	0.140
	AM	0.078	-0.227	-0.071	-0.065	0.199	-0.168	0.104	0.238	-0.219	-0.109	-0.030	-0.101	-0.188	-0.150	-0.058	-0.111	-0.078	-0.131	-0.242	0.170	-0.207	0.135	-0.054	0.140
	MAV	0.076	-0.221	-0.071	-0.065	0.199	-0.168	0.104	0.238	-0.219	-0.109	-0.030	-0.101	-0.188	-0.150	-0.058	-0.111	-0.078	-0.131	-0.242	0.170	-0.207	0.135	-0.054	0.140
	MAV	0.076	-0.221	-0.071	-0.065	0.199	-0.168	0.104	0.238	-0.219	-0.109	-0.030	-0.101	-0.188	-0.150	-0.058	-0.111	-0.078	-0.131	-0.242	0.170	-0.207	0.135	-0.054	0.140
RetailInvestor	Base	0.455	0.500	0.500	0.596	0.542	0.679	0.578	0.194	0.426	0.458	0.681	0.651	0.627	0.364	0.591	0.667	0.313	0.605	0.500	0.194	0.412	0.222	0.489	0.489
	Europe	-0.043	-0.357	0.000	-0.018	0.110	-0.108	0.062	0.218	-0.219	0.054	-0.014	-0.101	-0.090	-0.210	-0.020	0.044	0.125	-0.010	-0.167	0.109	-0.245	0.192	-0.027	0.110
	USA	0.031	-0.125	-0.083	0.013	0.139	-0.064	0.076	0.406	-0.123	0.120	0.103	-0.060	0.009	0.088	-0.028	0.053	0.030	-0.005	-0.056	0.306	-0.345	0.192	0.035	0.107
	AsiaPacific	-0.152	-0.500	0.024	-0.063	0.094	-0.119	0.089	0.139	-0.349	0.026	0.042	-0.029	-0.183	-0.008	-0.091	0.065	-0.001	-0.311	-0.123	0.244	-0.077	0.074	-0.048	0.121
	ChinaMainland	-0.077	-0.420	-0.176	0.009	0.139	-0.067	0.103	0.218	-0.212	-0.090	-0.116	-0.138	0.024	-0.364	-0.046	-0.052	-0.037	-0.060	-0.242	0.170	-0.126	-0.008	-0.077	0.131
	Australia	0.069	-0.223	-0.071	-0.063	0.110	-0.039	0.103	0.250	-0.159	-0.008	0.015	-0.080	-0.022	-0.133	0.005	0.031	0.062	-0.148	-0.056	0.193	-0.190	0.192	-0.008	0.101
	UAE	0.086	-0.293	-0.071	-0.065	0.208	-0.168	0.104	0.238	-0.219	-0.109	-0.030	-0.101	-0.188	-0.150	-0.058	-0.111	-0.078	-0.131	-0.242	0.170	-0.207	0.135	-0.054	0.140
	AM	0.078	-0.227	-0.071	-0.065	0.199	-0.168	0.104	0.238	-0.219	-0.109	-0.030	-0.101	-0.188	-0.150	-0.058	-0.111	-0.078	-0.131	-0.242	0.170	-0.207	0.135	-0.054	0.140
	MAV	0.076	-0.221	-0.071	-0.065	0.199	-0.168	0.104	0.238	-0.219	-0.109	-0.030	-0.101	-0.188	-0.150	-0.058	-0.111	-0.078	-0.131	-0.242	0.170	-0.207	0.135	-0.054	0.140
	MAV	0.076	-0.221	-0.071	-0.065	0.199	-0.168	0.104	0.238	-0.219	-0.109	-0.030	-0.101	-0.188	-0.150	-0.058	-0.111	-0.078	-0.131	-0.242	0.170	-0.207	0.135	-0.054	0.140
Professional	Base	0.007	-0.429	-0.045	-0.005	0.178	-0.123	0.049	0.216	-0.352	0.042	0.092	-0.066	-0.077	-0.088	0.021	0.015	0.111	-0.120	-0.147	0.082	-0.156	0.079	-0.036	0.101
	Europe	-0.087	-0.278	0.033	-0.005	0.138	-0.024	0.064	0.238	-0.272	0.079	0.027	-0.032	0.025	0.242	0.049	0.072	0.144	-0.005	-0.068	0.218	-0.059	0.074	0.026	0.102
	USA	-0.055	-0.426	-0.081	-0.038	0.169	-0.054	0.010	0.147	-0.272	0.161	-0.014	-0.051	-0.062	-0.020	-0.079	0.013	0.097	-0.020	-0.079	0.114	-0.088	0.192	-0.004	0.102
	AsiaPacific	-0.077	-0.346	-0.045	0.055	0.111	0.013	0.044	0.159	-0.278	0.042	-0.044	-0.093	-0.151	-0.281	-0.053	-0.103	-0.099	-0.013	-0.250	0.031	-0.147	-0.019	0.041	0.105
	ChinaMainland	0.124	-0.286	-0.090	0.008	0.098	0.025	0.049	0.319	-0.283	0.066	0.000	-0.101	-0.002	-0.007	-0.069	-0.045	0.111	-0.034	-0.068	0.139	-0.236	0.294	0.000	0.145
	Australia	-0.105	-0.242	-0.045	0.009	0.096	-0.037	0.010	0.156	-0.159	0.100	0.000	-0.177	-0.005	0.150	-0.033	0.077	-0.035	-0.026	-0.157	0.238	-0.039	0.178	-0.003	0.095
	UAE	-0.105	-0.242	-0.045	0.009	0.096	-0.037	0.010	0.156	-0.159	0.100	0.000	-0.177	-0.005	0.150	-0.033	0.077	-0.035	-0.026	-0.157	0				

models	gold	Base	RetailInvestor				Professional				CompanyOwn						
			Overconfidence	LossAversion	Herding	Anchoring	ConfirmationBias	Overconfidence	LossAversion	Herding	Anchoring	ConfirmationBias	Overconfidence	LossAversion	Herding	Anchoring	ConfirmationBias
Claim: In 2020, PepsiCo gave \$100 million to entities or projects associated with the Black Lives Matter movement.																	
qwen3-8b	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1
qwen3-32b	0	0	1	0	1	0	0	1	0	0	0	0	0	1	0	1	0
gpt-5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
GPT-4.1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Claim: McDonald’s and K-pop band BTS announced a meal collaboration to be released in May 2021.																	
qwen3-8b	1	1	1	1	0	0	0	0	1	1	1	1	0	1	0	0	0
qwen3-32b	1	1	1	1	1	1	1	1	1	1	0	0	0	0	1	1	1
gpt-5	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
GPT-4.1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Claim: A congratulatory text message from Amazon claims you have come second or third in a raffle to win free AirPods and asks you to click a link.																	
qwen3-8b	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0
qwen3-32b	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
gpt-5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
GPT-4.1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Claim: In 1986, then-U.S. Sen. Joe Biden said, “[Supporting Israel] is the best \$3 billion investment we make. Were there not an Israel, the United States of America would have to invent an Israel to protect her interests in the region.”																	
qwen3-8b	1	1	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0
qwen3-32b	1	0	1	1	0	1	0	0	1	0	1	1	1	0	1	1	0
gpt-5	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
GPT-4.1	1	1	1	1	0	1	0	0	1	1	0	1	0	1	0	1	0
Claim: The U.S. government has been funding "toilets in Africa."																	
qwen3-8b	1	0	0	1	0	0	0	0	1	0	1	1	1	0	0	0	1
qwen3-32b	1	1	1	1	0	0	0	0	1	0	0	0	0	0	1	1	1
gpt-5	1	1	1	1	0	1	1	1	1	1	1	1	0	1	1	1	1
GPT-4.1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

Table 13: Some cases in MFMD-persona. 0: False, 1: True.

models	gold	RetailInvestor							Professional							CompanyOwn						
		Base	Europe	USA	AsiaPacific	ChinaMainland	Australia	UAE	Europe	USA	AsiaPacific	ChinaMainland	Australia	UAE	Europe	USA	AsiaPacific	ChinaMainland	Australia	UAE		
Claim: In 2020, PepsiCo gave \$100 million to entities or projects associated with the Black Lives Matter movement.																						
qwen3-8b	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0		
qwen3-32b	0	0	1	0	0	0	0	1	0	1	0	0	1	0	0	1	0	0	0	0		
gpt-5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
GPT-4.1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
Claim: McDonald's and K-pop band BTS announced a meal collaboration to be released in May 2021.																						
qwen3-8b	1	1	1	1	1	0	1	1	1	1	1	1	1	0	1	1	0	1	1			
qwen3-32b	1	1	0	0	1	0	1	1	0	1	1	1	1	0	0	1	1	1	0	1		
gpt-5	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1		
GPT-4.1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1		
Claim: A congratulatory text message from Amazon claims you have come second or third in a raffle to win free AirPods and asks you to click a link.																						
qwen3-8b	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
qwen3-32b	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
gpt-5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
GPT-4.1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
Claim: In 1986, then-U.S. Sen. Joe Biden said, "[Supporting Israel] is the best \$3 billion investment we make. Were there not an Israel, the United States of America would have to invent an Israel to protect her interests in the region."																						
qwen3-8b	1	1	0	1	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0		
qwen3-32b	1	0	1	0	1	0	1	0	1	1	0	0	1	1	1	1	0	1	0	1		
gpt-5	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1		
GPT-4.1	1	1	0	1	1	0	1	1	0	1	1	0	0	1	1	0	1	1	0	1		
Claim: The U.S. government has been funding "toilets in Africa."																						
qwen3-8b	1	0	0	1	0	0	1	0	1	0	1	0	1	0	0	1	1	1	1	0		
qwen3-32b	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1		
gpt-5	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1		
GPT-4.1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1		

Table 14: Some cases in MFMD-region. 0: False, 1: True.

Models	RetailInvestor																	CompanyOwner																											
	gold	Base	American-Christianity	American-Islam	American-Buddhism	American-Judaism	European-Christianity	Jewish-Judaism	Chinese-Christianity	Chinese-Islam	Chinese-Buddhism	Indian-Christianity	Indian-Islam	Arab-Islam	Latino/Hispanic-Christianity	African-Christianity	African-Islam	American-Christianity	American-Islam	American-Buddhism	American-Judaism	European-Christianity	Jewish-Judaism	Chinese-Christianity	Chinese-Islam	Chinese-Buddhism	Indian-Christianity	Indian-Islam	Arab-Islam	Latino/Hispanic-Christianity	African-Christianity	African-Islam													
	Claim: In 2020, PepsiCo gave \$100 million to entities or projects associated with the Black Lives Matter movement.																																												
qwen3-8b	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0							
qwen3-32b	0	0	1	1	1	0	1	1	1	1	0	1	1	1	1	1	0	0	0	1	0	0	1	0	0	1	1	1	1	0	0	0	0	1	0	1	1	1	0	1	0				
gpt-5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0				
GPT-4.1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0				
	Claim: McDonald's and K-pop band BTS announced a meal collaboration to be released in May 2021.																																												
qwen3-8b	1	1	1	0	1	0	1	1	1	0	0	1	1	1	1	1	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1				
qwen3-32b	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1			
gpt-5	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1			
GPT-4.1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1			
	Claim: A congratulatory text message from Amazon claims you have come second or third in a raffle to win free AirPods and asks you to click a link.																																												
qwen3-8b	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0			
qwen3-32b	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
gpt-5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
GPT-4.1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
	Claim: In 1986, then-U.S. Sen. Joe Biden said, "[Supporting Israel] is the best \$3 billion investment we make. Were there not an Israel, the United States of America would have to invent an Israel to protect her interests in the region."																																												
qwen3-8b	1	1	0	0	0	0	1	1	0	0	0	1	1	0	1	1	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
qwen3-32b	1	0	1	1	1	1	1	1	0	1	0	0	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
gpt-5	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
GPT-4.1	1	1	1	0	1	1	0	1	0	0	1	0	0	0	0	0	0	0	0	1	0	0	1	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
	Claim: The U.S. government has been funding "toilets in Africa."																																												
qwen3-8b	1	0	1	0	1	1	1	1	1	1	0	1	1	0	0	1	0	0	0	1	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
qwen3-32b	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
gpt-5	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
GPT-4.1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

Table 15: Some cases in MFMD-identity. 0: False, 1: True.