

# Probing Multimodal Large Language Models on Cognitive Biases in Chinese Short-Video Misinformation

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## Abstract

Short-video platforms have become major channels for misinformation, where deceptive claims frequently leverage visual experiments and social cues. While Multimodal Large Language Models (MLLMs) have demonstrated impressive reasoning capabilities, their robustness against misinformation entangled with cognitive biases remains under-explored. In this paper, we introduce a comprehensive evaluation framework using a high-quality, manually annotated dataset of 200 short videos spanning four health domains. This dataset provides fine-grained annotations for three deceptive patterns—experimental errors, logical fallacies, and fabricated claims—each verified by evidence such as national standards and academic literature. We evaluate eight frontier MLLMs across five modality settings. Experimental results demonstrate that Gemini-2.5-Pro achieves the highest performance in the multimodal setting with a belief score of 71.5/100, while o3 performs the worst at 35.2. Furthermore, we investigate social cues that induce false beliefs in videos and find that models are susceptible to biases like authoritative channel IDs.

## 1 Introduction

Short-video platforms such as Douyin<sup>1</sup> and Kuaishou<sup>2</sup> have emerged as primary channels for information dissemination, yet they simultaneously facilitate the rapid spread of misinformation. Unlike text-based content, video misinformation leverages persuasive audiovisual cues, professional aesthetics, and plausible yet unverified experiments to enhance its deceptive power and virality. While recent Multimodal Large Language Models (MLLMs) excel on visual and textual understanding benchmarks (Yue et al., 2024; Liu et al., 2024), their behaviors remain poorly understood

when confronted with the real-world noise and social cues inherent in short videos.

While misinformation detection in text is well-established (Shu et al., 2020; Thorne et al., 2018), benchmarks have recently expanded to multimodal contexts, including text-image, speech, and video, such as FMNV (Wang et al., 2025b), FakeVV (Zhang et al., 2025), and FakeSV (Qi et al., 2023). However, existing studies primarily focus on fake news detection (Chen et al., 2025; Bu et al., 2024; Wang et al., 2024; Kumari et al., 2024; Yin et al., 2025; Yang et al., 2023; Palod et al., 2019; Papadopoulou et al., 2019; Guo et al., 2024), which often requires external sources for verification. This reliance on news data limits the capacity to evaluate logical reasoning and falsifiability. For example, a claim such as “an earthquake occurred in the middle of the Pacific yesterday” cannot be effectively falsified through internal logical consistency or commonsense analysis alone. Furthermore, other benchmarks are restricted to narrow domains such as COVID-19 (Shang et al., 2025; Liu et al., 2023; Shang et al., 2021; Serrano et al., 2020) or cancer (Hou et al., 2019), which are insufficient for a comprehensive evaluation.

This paper analyzes the capability of MLLMs to identify misinformation in short videos and diagnose the underlying causes of errors. We introduce a carefully annotated dataset of 200 videos spanning four domains. Unlike existing benchmarks that rely on synthesized data or broad channel-level heuristics (Li et al., 2022; Cao et al., 2025; You et al., 2022; Hussein et al., 2020), we curate content from professional debunking sources that provide empirical evidence, including research papers and national standards. We rigorously verify this evidence and categorize misinformation into three reasoning failure types—experimental errors, logical fallacies, and fabricated claims—enabling a systematic analysis of model vulnerabilities from a cognitive perspective.

<sup>1</sup><https://www.douyin.com/>

<sup>2</sup><https://www.kuaishou.com/>

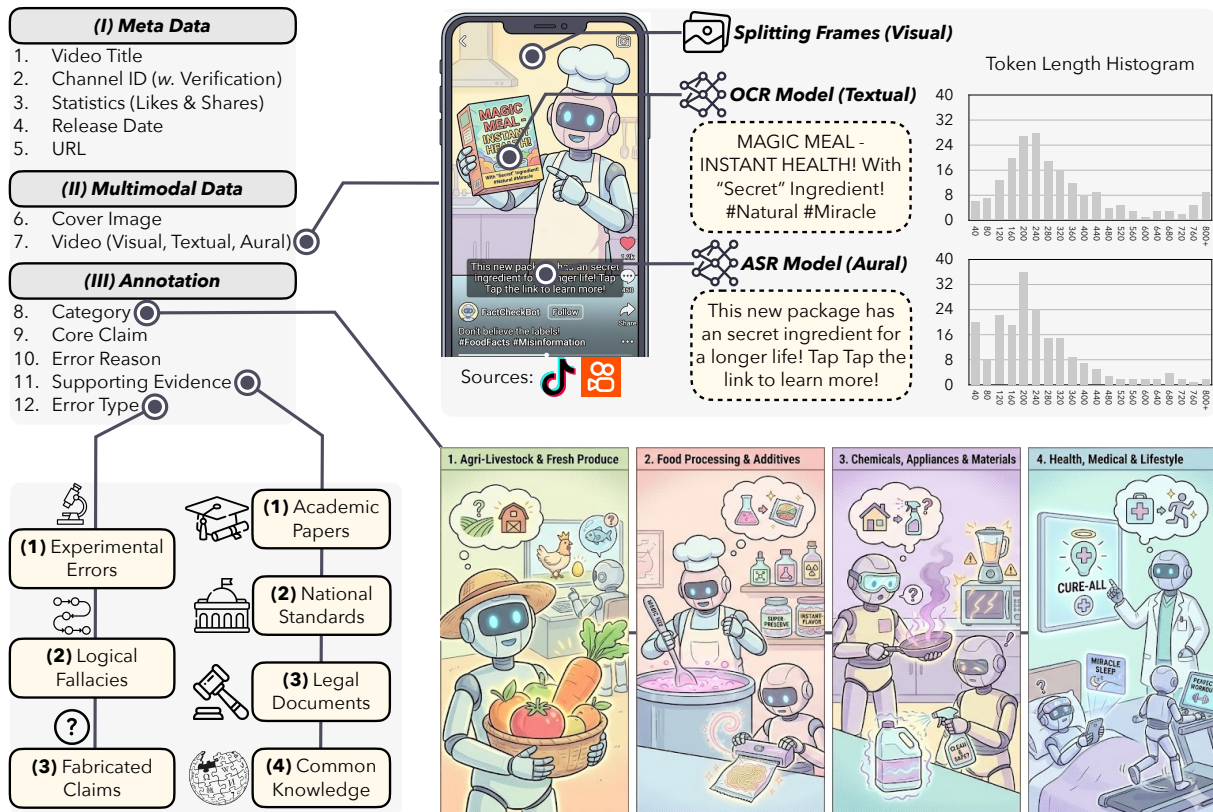


Figure 1: Overview of the data structure. *Upper-left*: The high-quality dataset consists of twelve fields. *Upper-right*: Videos from Douyin and Kuaishou are processed into visual, textual, and aural modalities, with histograms depicting token length distributions. *Lower-left*: Misinformation is annotated with detailed error reasons, supporting evidence, and error types. *Lower-right*: The dataset is categorized into four major public health domains. Note: grammatical errors, such as “an secret,” are intentional reflections of the original audio noise and actual ASR output.

To systematically investigate MLLM epistemics and belief formation in this scenario, we further collect video metadata, including engagement (shares and likes) statistics and channel verification status. We process the collected videos across multiple modalities: (1) *Visual* via splitting frames, (2) *Textual*, the on-screen text via Optical Character Recognition (OCR), and (3) *Aural*: the transcripts via Automatic Speech Recognition (ASR). Our research investigates the following three core questions: (1) **Modality Importance**: Which modality is most critical for rumor detection; (2) **Reasoning Path**: Whether model reasoning aligns with human-annotated, evidence-based logic paths; (3) **Cognitive Bias**: To what extent do models mirror human cognitive biases?<sup>3</sup> We employ experimental psychology concepts to examine the “herd effect” across varying popularity metrics and “authority bias” by manipulating channel identities (*e.g.*, official governmental vs. individual accounts).

<sup>3</sup>The systematic patterns of deviation from norm or rationality in judgment, specifically where external social cues override internal logical or evidence-based evaluation.

We evaluate eight frontier MLLMs under controlled input settings. To capture nuanced performance across modalities, we employ a 7-level Likert scale for trustworthiness scores rather than binary correctness. Our results reveal that multimodal inputs do not consistently improve belief judgments and are often surpassed by visual context alone. Furthermore, while Gemini-2.5-Pro achieves a belief score of 71.5/100, other models exhibit systematic label biases; *e.g.*, Qwen models frequently trust the videos regardless of correctness; o3 tends to be conservative by withholding full trust from any video. Regarding cognitive biases, we observe both popularity and authority effects: models gain higher performance as video engagement (*e.g.*, likes or shares) increases and tend to trust videos from highly authoritative channels regardless of factual accuracy. Our findings highlight critical limitations in the reasoning of current MLLMs under realistic short-video conditions. We have released our evaluation code via GitHub<sup>4</sup>

<sup>4</sup><https://github.com/penguinnnnn/Fine-VDK>

and dataset via HuggingFace<sup>5</sup> to facilitate the development of more resilient, fact-aware models.

## 2 Methods

### 2.1 Collecting Data and Ground-Truth

We curate a balanced dataset comprising 200 short videos, equally divided between misinformation ( $n = 100$ ) and truthful content ( $n = 100$ ). The data collection process focuses on high-quality ground-truth verification and diverse error patterns.

**Misinformation Collection.** To ensure the reliability of our labels, we first identify 100 debunking cases from professional fact-checking channels on Bilibili<sup>6</sup> and Douyin. These cases provide explicit evidence refuting specific claims. Based on these debunking points, we retrieve the original misinformation videos from Douyin and Kuaishou, spanning four thematic categories.

**Evidence and Error Taxonomy.** For each misinformation video, we manually reconstruct the underlying logical chain and summarize their error rationales. We further collect the supporting evidence provided by fact-checkers and classify them into four types: (1) *Academic Papers*, (2) *National Standards*, (3) *Legal Documents*, and (4) *Common Knowledge/Wikipedia*. By cross-referencing the logical chains with the verified evidence, we define a taxonomy of three distinct error patterns:

- **Experimental Errors** ( $n = 16$ ): The depicted experiments lack scientific rigor, employ flawed methodologies, or are even irrelevant to the core claim.
- **Logical Fallacies** ( $n = 55$ ): The argumentative structure used to substantiate the claim is fundamentally flawed or non-sequitur.
- **Fabricated Claims** ( $n = 29$ ): The assertions or supporting data are entirely groundless or invented by the speaker.

**Truthful Set Construction.** To construct a comparable control group, we extract verified claims from Piyao,<sup>7</sup> a centralized Chinese internet rumor-refuting platform. We then retrieve 100 corresponding promotional or educational videos from Douyin and Kuaishou that align with these verified claims. This ensures the truthful set shares a similar topical

<sup>5</sup><https://huggingface.co/datasets/penguin-G/Fine-VDK>.

<sup>6</sup><https://www.bilibili.com/>

<sup>7</sup><https://www.piyao.org.cn/>

distribution and visual style with the misinformation set. For a detailed comparison with existing benchmarks, please refer to §5.

### 2.2 Annotation and Categorization

**Topic Taxonomy.** To facilitate a fine-grained analysis of MLLM performance across different domains, we manually categorize the dataset into four thematic domains based on the video content:

- **Agri-Livestock & Fresh Produce** ( $n = 41$ ): Covering primary agricultural products including fruits, vegetables, grains, oil crops, fungi, and animal-derived products such as meat, eggs, and seafood.
- **Food Processing & Additives** ( $n = 44$ ): Focusing on food preservation, culinary technologies, food additives, seasonings, and processed goods (e.g., dairy, beverages, and ready-to-eat meals).
- **Chemicals, Appliances & Materials** ( $n = 37$ ): Concerning food-contact materials (plastics, metals), cookware, kitchen appliances, and household chemical cleaners.
- **Health, Medical & Lifestyle** ( $n = 78$ ): Encompassing medical misinformation, disease prevention, and the health impacts of lifestyle choices such as exercise and sleep.

**Social Metadata.** For each video, we extract a comprehensive set of metadata to support downstream experiments: (i) cover image, (ii) video title, (iii) channel ID, (iv) popularity statistics (likes and shares), (v) release date, and (vi) the original URL. The dataset exhibits significant social impact; popularity metrics for likes range from a median of 9.1k to a maximum of 1.4m (mean: 63k), while shares range from a median of 3.8k to a maximum of 660k (mean: 52k).

**Channel Verification.** Furthermore, we annotate each *channel ID* with its official verification status as defined by Douyin’s platform standards, serving as a proxy for institutional authority:

- **Unverified** ( $n = 91$ ): Accounts without official authentication.
- **Yellow-Individual** ( $n = 43$ ): Verified public figures, domain experts, or influential content creators.
- **Blue-Enterprise** ( $n = 42$ ): Verified commercial entities or corporate brands.

- **Red-Organization** ( $n = 24$ ): Verified government agencies, state-affiliated media, or non-profit organizations.

### 2.3 Pre-Processing and Semantic Distillation

To ensure data quality and focus on core argumentative content, we manually download the raw videos while trimming advertisements, introductory sequences, and irrelevant segments. The processed videos have an average duration of  $53.5 \pm 39.3$  seconds (median: 44.5s; range: [2.9, 278.3]s). We then decompose each video into three modalities:

**Visual Modality.** To facilitate processing by MLLMs, we sample frames at a rate of 0.5 FPS (one frame every two seconds). For videos exceeding 64 seconds, we apply uniform downsampling to cap the input at 32 frames. This resulted in an average of  $21.8 \pm 9.1$  frames per video (median: 19.5; range: [2, 32]).

**Textual Modality.** We extract on-screen text using a commercial OCR model<sup>8</sup>, followed by manual verification and correction. To eliminate redundancy caused by persistent on-screen elements, we record only the first occurrence of each unique text instance. The final OCR sequences have an average length of  $229.0 \pm 175.4$  tiktoken<sup>9</sup> tokens (median: 187.5; range: [0, 1014]).

**Aural Modality.** Audio tracks are transcribed using an ASR model<sup>10</sup> and manually audited for accuracy. Transcripts do not constitute a simple subset of the textual modality, as many videos lack subtitles and existing ones often incorporate abbreviations to circumvent platform censorship. For videos containing only background music or no speech, the transcript length is recorded as zero. The transcripts average  $306.0 \pm 239.0$  tiktoken tokens (median: 238.0; range: [0, 1685]).

**Summary.** Our data structure is illustrated in Fig. 1, which also shows the histograms of token lengths for Textual and Aural modalities.

## 3 Experiments

### 3.1 Experimental Setup

**Model Selection** We evaluate eight frontier MLLMs to ensure a comprehensive assessment

<sup>8</sup><https://ai.aliyun.com/ocr>

<sup>9</sup><https://pypi.org/project/tiktoken/>

<sup>10</sup><https://ai.aliyun.com/nls/filetrans/>

across different model families and architectures. These include: (1) OpenAI: GPT-4o (2024-11-20) (Hurst et al., 2024) and o3 (2025-04-16) (OpenAI, 2025); (2) Google: Gemini-2.5 Flash and Pro (Kavukcuoglu, 2025); (3) Alibaba: the open-source Qwen2.5-VL-72B-Instruct (Bai et al., 2025) and the proprietary Qwen-VL-Max (2025-04-08) (Team, 2024); (4) Anthropic: Claude-4-Sonnet (2025-05-14) (Anthropic, 2025); and (5) ByteDance: Seed-1.6-Thinking (2025-07-15) (ByteDance, 2025). We set the temperature parameter to zero whenever available and keep other hyper-parameters as default.

**Input Configurations.** To disentangle the contribution of different modalities to the models’ reasoning, we define five experimental settings: (i) Claim: only the manually labeled core claims, (ii) Textual: only the screen texts extracted via OCR, (iii) Aural: only the transcripts extracted via ASR, (iv) Visual: only the sampled frames, and (v) Multimodal: combining frames and transcripts.

**Evaluation Metrics.** We leverage Chain-of-Thought (CoT) prompting to guide models in identifying misinformation. Models are instructed to provide a judgment on a 7-point Likert scale, where 1 indicates high confidence that the content is factual (no misinformation) and 7 indicates high confidence that it is misinformation, with 4 as the neutral point. All prompts used in this paper are provided in Appendix C. To quantify model performance and its alignment with ground truth, we define a normalized Belief Score (BS) which only rewards the skepticism in misinformation (where Label is False and  $r > 4$ ) or belief toward factual content (where Label is True and  $r < 4$ ). Let  $r \in \{1, \dots, 7\}$  denote the raw rating provided by the model. The BS is calculated as follows:

$$BS = \max\left\{\begin{array}{l} \frac{r-4}{3} \text{ if Label is False} \\ \frac{4-r}{3} \text{ if Label is True} \end{array}, 0\right\}. \quad (1)$$

### 3.2 Main Results

Table 1 presents the results across the five input settings. While models consistently achieve peak performance under the “Claim” setting, this serves as a reference rather than a measure of model’s own capability, as manual claim extraction simplifies the problem by eliminating noise and distractors that models would otherwise need to identify.

**Comparison Among Models.** Our analysis reveals several key findings: (1) **Gemini-2.5-Pro**

Model	Claim			Textual			Aural			Visual			Multimodal		
	F	T	All	F	T	All	F	T	All	F	T	All	F	T	All
GPT-4o-20241120	63.3	71.7	67.5	34.7	<b>80.0</b>	57.3	32.7	<b>71.3</b>	52.0	26.7	68.0	47.3	46.0	72.7	59.3
o3-20250416	64.0	<u>46.3</u>	55.2	53.0	<u>15.0</u>	<u>34.0</u>	40.3	<u>5.7</u>	<u>23.0</u>	55.7	<u>25.7</u>	40.7	54.0	<u>16.3</u>	<u>35.2</u>
Gemini-2.5-Flash	79.7	70.0	74.8	63.0	50.3	56.7	56.0	34.3	45.2	78.3	56.7	67.5	71.0	58.0	64.5
Gemini-2.5-Pro	84.7	73.3	<b>79.0</b>	<b>73.0</b>	75.0	<b>74.0</b>	<b>60.0</b>	52.7	<b>56.3</b>	<b>82.0</b>	77.3	<b>79.7</b>	<b>77.7</b>	66.3	<b>71.5</b>
Qwen-VL-Max	52.3	59.0	55.7	42.7	68.3	55.5	49.0	61.3	55.2	46.3	74.3	60.3	<u>21.7</u>	<b>80.0</b>	50.8
Qwen-2.5-VL	48.0	59.7	<u>53.8</u>	<u>33.0</u>	73.0	53.0	<u>15.7</u>	61.0	38.3	0.0	<b>89.0</b>	44.5	24.7	79.7	52.2
Claude-Sonnet-4	<u>47.3</u>	<b>76.7</b>	62.0	39.0	57.7	48.3	39.7	49.0	44.3	23.3	39.3	<u>31.3</u>	35.7	59.3	47.5
Seed-1.6-Thinking	<b>90.0</b>	59.0	74.5	44.0	77.7	60.8	41.7	64.3	53.0	51.7	90.3	71.0	61.7	69.3	65.5
<b>Average</b>	66.2	64.5	65.3	47.8	62.1	55.0	41.9	50.0	45.9	45.5	65.1	55.3	48.9	62.7	55.8

Table 1: Belief Scores (BS) of eight models across five input settings on false and true video subsets. **Bold** and Underlined values denote the best and worst performance per column, respectively.

Model	Agri-Livestock & Fresh Produce			Food Processing & Additives			Chemicals, Appliances & Materials			Health, Medical & Lifestyle		
	F	T	All	F	T	All	F	T	All	F	T	All
GPT-4o-20241120	29.3	51.0	40.2	46.0	73.3	59.7	27.3	65.3	46.3	72.3	82.0	<b>77.2</b>
o3-20250416	52.7	<u>13.3</u>	33.0	53.0	<u>0.0</u>	<u>26.5</u>	42.3	<u>25.7</u>	<u>34.0</u>	62.7	<u>14.7</u>	38.7
Gemini-2.5-Flash	61.7	49.0	55.3	72.7	66.7	69.7	51.7	47.3	49.5	<b>87.3</b>	64.7	76.0
Gemini-2.5-Pro	<b>66.7</b>	<b>71.0</b>	<b>68.8</b>	<b>83.0</b>	86.7	<b>84.8</b>	<b>57.7</b>	64.0	<b>60.8</b>	86.0	64.3	75.2
Qwen-VL-Max	11.7	44.3	28.0	<u>21.3</u>	80.0	50.7	<u>0.0</u>	78.3	39.2	46.0	<b>90.7</b>	68.3
Qwen-2.5-VL-72B	<u>5.0</u>	46.7	<u>25.8</u>	26.3	73.3	49.8	9.0	<b>86.0</b>	47.5	50.0	86.3	68.2
Claude-Sonnet-4	20.7	44.3	32.5	40.3	60.0	50.2	36.3	55.0	45.7	<u>44.3</u>	65.3	54.8
Seed-1.6-Thinking	64.0	33.3	48.7	62.3	<b>100.0</b>	81.2	45.3	57.7	51.5	65.3	82.0	73.7
<b>Average</b>	39.0	44.1	41.5	50.6	67.5	59.1	33.7	59.9	46.8	64.3	68.8	66.5

Table 2: Belief Scores (BS) of eight models across four domains on false and true video subsets using the *Multimodal* setting. **Bold** and Underlined values denote the best and worst performance per column, respectively. Results using the *Claim* setting is shown in Table 10 in Appendix B.

achieves the highest performance among the eight models across all settings. Its performance remains balanced across both true and false subsets, demonstrating no significant weaknesses. (2) Several models exhibit systematic biases toward specific labels (false or true). In all cases where Gemini-2.5-Pro is surpassed (*i.e.*, GPT-4o in Textual and Aural settings, Qwen-2.5-VL in Visual, Qwen-VL-Max in Multimodal, and Claude-4 or Seed-1.6 in Claim settings), high scores on one subset consistently correlate with below-average scores on the other. This suggests these models do not fundamentally outperform Gemini-2.5-Pro but instead benefit from label bias. (3) **o3** performs poorly across all settings, primarily due to remarkably low scores on the true video subset. This stems not from a bias toward “false” predictions—as its false subset performance remains mediocre—but from a conservative reasoning style. Analysis of its CoT outputs suggests that o3 avoids providing affirmative judgments regard-

ing video correctness. (4) **Qwen models** exhibit a systematic bias toward “true” predictions, resulting in high scores on the true subset but significantly lower performance on the false subset.

**Comparison Among Modalities.** The modalities exhibit specific overlaps: textual data partially encompasses aural information through subtitles, while visual data contains textual elements, though this overlap is limited by the 32-frame sampling rate. The multimodal setting integrates both streams, capturing visual features, on-screen text, and transcripts. As shown in Table 1, average performance is comparable across textual, visual, and multimodal settings, while aural performance is approximately 10 points lower. Furthermore, the bias of Qwen models toward “true” predictions mentioned above is amplified by the presence of visual content in the visual and multimodal settings, compared to textual or aural modalities.

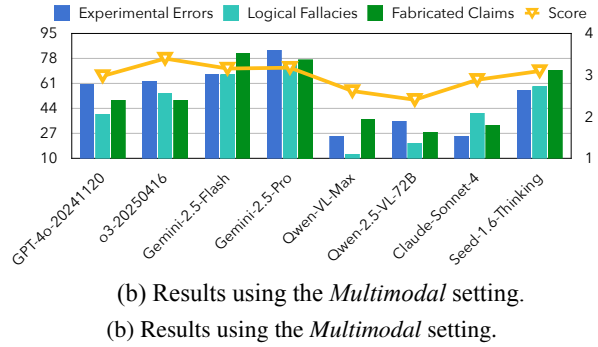
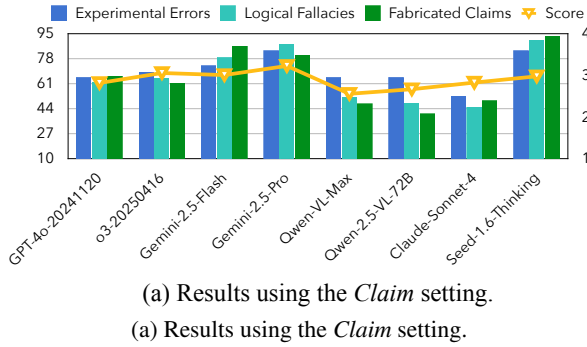


Figure 2: Belief Scores (BS) of eight models across three error types on the false video subset. Yellow “Score” lines indicate the presence of annotated error reasons in the model CoT processes, rated by Gemini-2.5-Pro.

**Comparison Among Domains.** Tables 2 and 10 present the results across four domains. The Health, Medical, and Lifestyle domain proves the least challenging for models, whereas the Agri-livestock and Fresh Produce domain remains the most difficult. This disparity likely stems from the prevalence of widespread general health rumors within the health domain that models have encountered during pre-training, whereas other domains involve claims about recently released products that fall outside the training corpus. Furthermore, the Chemicals, Appliances, and Materials domain exhibits the most significant performance imbalance between the false and true subsets. This disparity stems from claims that were historically accurate but have since been rendered obsolete by technological advancements. For instance, a misinformation video (ID: 39) claims that nonstick cookware coatings contain bioaccumulative toxic substances; while previously true, modern materials have resolved this issue. Qwen models, unaware of these updates, fail to identify such misinformation. A similar failure occurs for video (ID: 8), which incorrectly claims that PET plastic bottles cannot be reused due to the release of plasticizers when heated.

### 3.3 Results by Error Types

Figure 2 illustrates the performance across three error types within the false video subset. We employ Gemini-2.5-Pro to evaluate model’s CoT process, assessing whether models successfully infer human-annotated error reasons. Gemini assigns a four-level score based on the coverage of the actual error: (1) no coverage, (2) partial coverage, (3) near-complete coverage, and (4) complete coverage. Results indicate that while belief scores are consistently higher in the Claim setting, reasoning ratings are superior in the Multimodal setting.

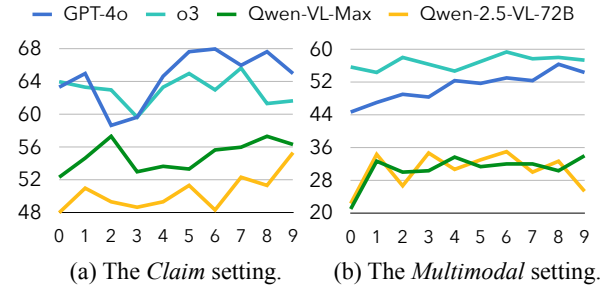


Figure 3: Belief Scores (BS) of four models with different levels of popularity statistics (views, likes, comments, shares) on the false video subset.

This suggests that the additional information provided in the multimodal context enables models to more accurately identify the underlying reasons for misinformation. Notably, logical fallacies remain the most challenging to identify, yielding the lowest performance in the Multimodal setting (45.9) compared to other error types (51.8 and 53.0). Conversely, performance is more uniform across error types in the Claim setting, likely because human-extracted inputs simplify the task.

## 4 Cognitive Bias Analyses

Previous experiments provide the models only with contexts directly related to logical reasoning, excluding distractors such as channel IDs or popularity metrics. This section investigates model behavior in the presence of human cognitive biases to answer the research question: whether these distractor inputs alter model judgments.

### 4.1 Popularity Effect

This experiment examines the *Herd Effect* (or *Bandwagon Effect*), where individuals align with majority opinions or behaviors rather than their own judgment (Banerjee, 1992; Leibenstein, 1950). Re-

Model	Unverified			Individual			Enterprise			Organization			w. ID (All)		
	F	T	All	F	T	All	F	T	All	F	T	All	F	T	All
GPT-4o-20241120	70.7	74.0	72.3	38.0	67.7	52.8	50.0	91.0	70.5	50.0	<b>83.3</b>	<b>66.7</b>	61.7	78.3	70.0
o3-20250416	67.3	55.7	61.5	52.3	46.0	49.2	64.7	<u>50.0</u>	<u>57.3</u>	<u>22.3</u>	<u>46.3</u>	<u>34.3</u>	62.0	<u>49.7</u>	55.8
Gemini-2.5-Flash	85.3	<b>90.0</b>	87.7	69.0	<u>42.7</u>	55.8	<b>85.3</b>	92.3	<b>88.8</b>	<b>55.7</b>	63.0	59.3	81.3	72.0	76.7
Gemini-2.5-Pro	92.3	87.7	<b>90.0</b>	<b>81.0</b>	61.0	71.0	73.0	<b>93.7</b>	83.3	<b>55.7</b>	76.0	65.8	<b>85.3</b>	79.3	82.3
Qwen-VL-Max	60.3	<u>52.0</u>	56.2	38.0	53.0	45.5	50.0	71.7	60.8	27.7	72.3	50.0	53.7	61.0	57.3
Qwen-2.5-VL-72B	<u>56.7</u>	54.3	<u>55.5</u>	<u>31.0</u>	50.7	<u>40.8</u>	<u>48.0</u>	71.7	59.8	27.7	72.3	50.0	<u>50.0</u>	61.0	<u>55.5</u>
Claude-Sonnet-4	58.3	87.7	73.0	26.3	67.7	47.0	<u>48.0</u>	91.0	69.5	<u>22.3</u>	81.3	51.8	<u>50.0</u>	<b>81.7</b>	65.8
Seed-1.6-Thinking	<b>92.7</b>	71.7	82.2	<b>81.0</b>	<b>69.0</b>	<b>75.0</b>	75.0	92.3	83.7	33.3	77.7	55.5	84.7	77.3	<b>81.0</b>
<b>Average</b>	<b>73.0</b>	<b>71.6</b>	<b>72.3</b>	<b>52.1</b>	<b>57.2</b>	<b>54.6</b>	<b>61.8</b>	<b>81.7</b>	<b>71.7</b>	<b>36.8</b>	<b>71.5</b>	<b>54.2</b>	<b>66.1</b>	<b>70.0</b>	<b>68.1</b>

Table 3: Belief Scores (BS) of eight models across four channel verification statuses on false and true video subsets with channel IDs using the *Claim* setting. **Bold** and Underlined values denote the best and worst performance per column, respectively. Results without channel IDs are shown in Table 11 in Appendix B.

cent studies indicate that AI models are similarly susceptible to external social signals, often mirroring choices attributed to other (Liu et al., 2025c; Yang et al., 2024; Cho et al., 2025). In our study, high popularity metrics (e.g., 10M views) serve as a proxy for social endorsement. We hypothesize that the herd effect manifests as an increased model propensity to trust highly popular videos, even when the content contains misinformation.

We first aggregate the view, like, share, and comment counts for the top 10 most-liked videos in the false video subset, yielding values of 10M, 550K, 373K, and 50K, respectively. We scale these statistics by powers of ten across nine levels—ranging from a maximum of (10B, 550M, 373M, 50M) to a minimum of (100, 5, 3, 0)—and provide them as explicit prompts to GPT-4o, o3, Qwen-VL-Max, and Qwen-2.5-VL. Evaluations on the false video set under *Claim* and *Multimodal* settings (Fig. 3) reveal that high popularity does not decrease model belief scores; surprisingly, scores increase, suggesting that increased engagement metrics enhance model confidence in their initial judgments rather than inducing trust in misinformation.

## 4.2 Channel ID Effect

This experiment explore the *Authority Bias*, the tendency to accept statements from authoritative figures as more credible regardless of content (Milgram, 1963; Cialdini, 2007). AI models have been shown to exhibit such judgmental biases when acting as evaluators (Ye et al., 2025; Jin et al., 2024; Chen et al., 2024a). We hypothesize that models perceive verified channel IDs as more trustworthy than unverified ones, leading them to assign higher scores to videos associated with verified accounts.

We first reveal the corresponding channel ID

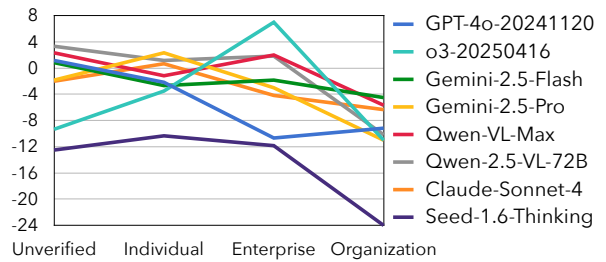


Figure 4: The difference ( $r_{\text{with\_ID}} - r_{\text{without\_ID}}$ ) rescaled by  $\frac{100}{3}$  across four verification statuses for eight models using the *Claim* setting and all video data. Results on the two subsets are provided in Fig. 6 in Appendix B.

for each video to the models using the *Claim* setting. Results across the four channel verification statuses are presented in Table 3 (with IDs) and Table 11 (without IDs). Performance on the false video subset consistently decreases for verified IDs compared to unverified ones regardless of whether channel IDs are provided, suggesting that verified accounts produce more deceptive content. The highest verification level (Organization) yields an average belief score of 36.8 on the false set—a significant reduction compared to Unverified accounts (73.0). This phenomenon persists across all models, including the best-performing Gemini-2.5-Pro. Furthermore, we perform a pairwise comparison of predicted scores with and without channel IDs to isolate the influence of ID presence. As shown in Fig. 4 and 6, a clear downward trend exists from the “Unverified” to “Organization” levels, indicating that model predictions are significantly influenced by authoritative IDs. These results demonstrate that the eight studied models exhibit authority bias in the context of short-video misinformation.

To verify that channel IDs exert an influence independent of their associated videos, we randomly

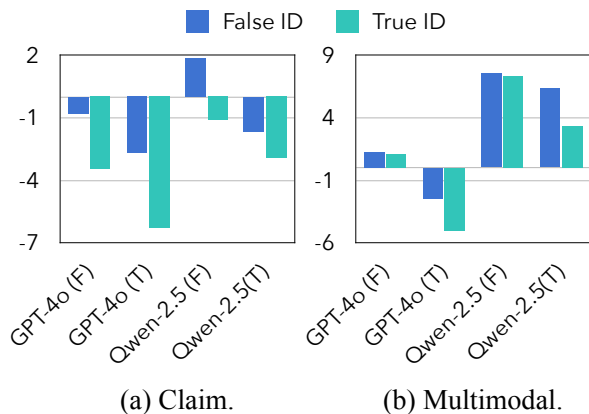


Figure 5: Average score decrease after using channel IDs from the false set (dark blue) and the true set (light blue) on the false (F) and true (T) video subsets.

permute the ID assignments. In this experiment, each video is paired with five IDs sampled from: (1) the false video set and (2) the true video set. Fig. 5 illustrates the average score decrease for GPT-4o and Qwen-2.5. We observe a consistent pattern where “True” IDs yield lower predicted scores than “False” IDs, regardless of the video’s ground truth, indicating that models give more positive judgments when seeing these “True” IDs. To investigate this behavior, we prompt the models to provide a binary reliability judgment for each channel ID (Dai et al., 2025). Results show that GPT-4o and Qwen-2.5 rate only 2.25% and 1.12% of IDs from the false set as reliable, compared to 28.8% and 19.2% for the “True” set. This indicates that implicit assessments of channel reliability significantly influence the models’ veracity decisions.

## 5 Related Work

**Video Understanding.** Evaluating the video analysis capabilities of MLLMs ability to analyze videos has been a central focus in AI research (Fang et al., 2024; Li et al., 2024; Fu et al., 2025; Chen et al., 2024b; Han et al., 2025; Wang et al., 2025a; Huang et al., 2024). Beyond models with native video support, various strategies have emerged for processing video inputs: Li et al. (2025) represent frames with semantic carrier tokens to preserve inter-frame context, while Kim et al. (2024) aggregate frames into a single composite image to maintain pixel-level temporal information. Additionally, Hong et al. (2024) leverage GPT-4o for keyframe extraction. To ensure generalizability, we adopt the standard practice of downsampling frames with a fixed rate limit (Ataallah et al., 2025).

**Misinformation Detection with AI.** Detecting misinformation remains a critical yet formidable challenge. While existing research in the text domain focuses on specific categories such as health-related misinformation (Tan et al., 2025; Garbarino and Bragazzi, 2024) and news (Liu et al., 2025b; Haupt et al., 2024), video-based misinformation presents unique difficulties due to the cross-modal separation of cues (Papadopoulou et al., 2019). Several datasets have been developed to address this: FMNV (Wang et al., 2025b) provides news videos across text, visual, and audio modalities, and MultiTec (Shang et al., 2025) contains TikTok short-videos centered on COVID-19. However, as discussed in §1, these benchmarks primarily target general news, whereas our dataset focuses on rumors supported by plausible “proof” to evaluate a model’s ability to identify underlying errors.

While Li et al. (2022) introduces a health-related dataset, the misleading content is synthesized by merging segments of authentic videos rather than being sourced from original platform dissemination, which limits its ecological validity. Other rumor-related studies (Cao et al., 2025; You et al., 2022) similarly lack fine-grained labels and manual verification of correctness. Our data are primarily collected via web crawling and lack both fine-grained annotations and rigorous verification, addressing this gap.

**Cognitive Biases in AI.** Researchers have used psychological framework (Liu et al., 2025a; Wu et al., 2025; Zhou et al., 2025b) to evaluate cognitive biases in AI models across textual and visual modalities, including herd effect (Cho et al., 2025), authority bias (Moon et al., 2025), in-group bias (Huang et al., 2025b), social desirability bias (Zhou et al., 2025a), anchoring bias (Echterhoff et al., 2024), confirmation bias (Chuang et al., 2024), illusory truth effect (Griffin et al., 2023), stereotype bias (Huang et al., 2025a), and halo effect (Liu et al., 2025c). Our study focuses on the two biases most relevant to the short-video context.

## 6 Discussions

**Sample Size.** While our dataset ( $n = 200$ ) is smaller than some automatically generated synthetic datasets, we prioritized annotation quality over quantity. The manual distillation of core claims, temporal trimming of videos, and categorization of error patterns (Experimental Errors, Logical Fallacies, or Fabricated Claims) re-

quire expert-level judgment that current automated pipelines cannot reliably replicate. We explicitly avoid drawing conclusions from atomic intersections (*e.g.*, Fabricated Claims within the Agri-Livestock category in the True video subset). Instead, we analyze marginal distributions to maintain statistical power, such as False vs. True, across domains (*e.g.*, Agri-Livestock vs. Health, or across error types (*e.g.*, Logical Fallacies vs. Fabricated Claims). To further address this issue, we conduct a statistical analysis confirming that the performance gaps between models are robust, even within the sub-categories. For instance, in the Agri-Livestock & Fresh Produce subset ( $n = 41$ ), we conducted a  $t$ -test between Gemini-2.5-Pro (Mean= 88.6, SD= 27.5) and GPT-4o (Mean=69.1, SD=32.0). The results reveal a significant difference ( $t = 2.96$ ,  $df = 40$ ,  $p = 0.0025$ ). This  $p$ -value ( $< 0.01$ ) demonstrates that the performance disparities we report are statistically significant and not artifacts of sample variance or data sparsity. The high “signal-to-noise” ratio in our high-quality data compensates for the smaller  $N$ .

**Conclusion** In this study, we present a comprehensive evaluation of MLLMs in the context of short-video misinformation detection. By curating a high-quality dataset of 200 videos from Kuaishou and Douyin—meticulously annotated with fine-grained error types and grounded in authoritative evidence—we established a rigorous benchmark for multimodal truth-seeking. Our systematic experiments reveal that: (1) While Gemini-2.5-Pro excels on the Multimodal setting, other models still suffer from biases towards certain labels (Qwen models and o3). (2) Models exhibit significant Herd Effects (driven by popularity metrics) and Authority Biases (driven by channel verification status). Our work facilitates the community on developing MLLMs that are not only capable of understanding multimodal content but are also resilient to the sophisticated deceptive tactics prevalent in modern social media.

## Limitations

**Linguistic and Cultural Specificity.** Our study primarily focuses on short-video content from the Simplified Chinese digital ecosystem (*i.e.*, Douyin and Kuaishou). While this may limit the direct transferability of the findings to other linguistic contexts, we believe this focus is justified for:

- **Scale and Impact:** Chinese is one of the most

widely spoken languages globally. The short-video platforms we studied have billions of active users, making them a significant frontier for the spread of misinformation.

- **Cultural Contextualization:** Misinformation is often culturally “sticky.” Many claims in our dataset—such as those involving specific food products or traditional lifestyle myths—are deeply rooted in the socio-cultural fabric of the Chinese community. Focusing on a single ecosystem allows for a deeper analysis of how LLMs navigate these culture-specific logical fallacies.

**Potential Data Contamination.** A common challenge in evaluating SOTA MLLMs is the risk of data contamination. Although the specific videos were recently collected, the underlying debunking facts (*e.g.*, national standards or scientific debunking of popular myths) might have existed in the models’ training corpora. This could lead to an overestimation of the models’ reasoning capabilities, as they might be retrieving memorized facts rather than performing zero-shot analysis.

**Granularity of Visual Perception.** Our frame sampling strategy (one frame per 2 seconds, max 32 frames) is designed to balance information density with the context window limits of MLLMs. However, this temporal downsampling might miss subtle visual manipulations or micro-experiments that occur in very short intervals. Future work could explore dynamic sampling rates based on the visual complexity of the video.

## Ethics Statements

**Researcher Stance and Intent.** Our study focuses on the systematic analysis of misinformation dissemination patterns rather than targeting or stigmatizing specific individuals. The categorization of content as misinformation is based on third-party fact-checkers and official debunking articles, and is intended solely for academic research. We explicitly state that this work is not intended to harass, defame, or incite any form of hostility toward the original creators. While our findings highlight the presence of inaccurate information, our ultimate goal is to develop effective multimodal systems. We believe that by understanding these patterns, we can better support systems that provide corrective feedback to creators, helping them improve the accuracy of their content and fostering a healthier information ecosystem.

**Copyright and Licensing.** Our dataset consists of publicly available short videos sourced from Douyin and Kuaishou. We acknowledge that the copyright of all original video content, including visual and audio elements, remains with the respective original creators. Our collection process followed the platforms' terms of service for research purposes. To balance research utility with intellectual property rights, we release the curated dataset (metadata and features) under a CC BY-NC 4.0 license, strictly limiting its use to non-commercial academic research. We provide a clear takedown protocol for any creator who wishes to have their content removed from our index.

**Use of AI Assistants.** LLMs were employed in a limited capacity for writing optimization. Specifically, the authors provided their own draft text to the LLM, which in turn suggested improvements such as corrections of grammatical errors, clearer phrasing, and removal of non-academic expressions. LLMs were also used to inspire possible titles. While the systems provided suggestions, the final title was decided and refined by the authors and is not directly taken from any single LLM output. In addition, LLMs were used as coding assistants during, providing code completion and debugging suggestions, but all final implementations and experimental design were carried out and verified by the authors. Importantly, LLMs were **NOT** used for generating research ideas or designing experiments. All conceptual contributions were fully conceived and executed by the authors.

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## A Further Analysis

### A.1 Lexical Cues in Claims

Table 4 presents the distribution of negative and affirmative claims across our video dataset. The false subset contains 16 negative and 84 affirmative claims, while the true subset consists of 62 and 38, respectively. Average performance across eight models in the claim-only setting indicates that negative claims consistently receive higher belief scores. To further analyze this trend, we manually invert each claim—transforming negations into affirmations and vice-versa—and flip the ground-truth labels. Notably, these reversed results show that converting affirmations to negations significantly increases belief scores, whereas transforming negations to affirmations leads to a decrease.

	False Set		True Set	
	Neg	Aff	Neg	Aff
<b>Counts</b>	16	84	62	38
<b>Original</b>	50.8	51.4	62.0	55.0
<b>Reverse</b>	35.3 (↓)	58.0 (↑)	58.7 (↓)	60.7 (↑)

Table 4: Average Belief Scores (BS) across eight models by the negation of affirmation in the claims. “Reverse” denotes negating the original claims, thus making Neg to Aff and Aff to Neg, also flipping the label.

### A.2 Multiple Runs

We evaluate our approach using GPT-4o over five runs in both the Claim and Multimodal settings. As shown in Table 5, performance fluctuations are minimal in the Claim setting and slightly more pronounced in the Multimodal setting, yet these variations do not compromise the robustness of our conclusions.

GPT-4o	R1	R2	R3	R4	R5	Mean $\pm$ Std
<i>Claim</i>						
False	63.3	61.3	61.0	61.3	61.0	61.6 $\pm$ 0.98
True	71.7	72.7	73.7	72.3	73.7	72.8 $\pm$ 0.87
All	67.5	67.0	67.3	66.8	67.3	67.2 $\pm$ 0.27
<i>Multimodal</i>						
False	44.7	47.3	44.0	49.3	47.7	46.6 $\pm$ 2.22
True	75.3	76.3	78.7	72.7	77.3	76.1 $\pm$ 2.27
All	60.0	61.8	61.3	61.0	62.5	61.3 $\pm$ 0.94

Table 5: Belief Scores (BS) of GPT-4o using the Claim and Multimodal settings with five runs.

Model	Claim	Transcript	Screen Text	Frame	Multimodal
GPT-4o-20241120	559	832.8	902.55	24178.17	24454.8
o3-20250416	659.24	951.66	1048.1	21575.47	21844.28
Gemini-2.5-Flash	681.36	1014.99	1161.53	6478.84	6681.91
Gemini-2.5-Pro	700.86	966.07	1058.08	6344.62	6567.76
Qwen-VL-Max	741.49	885.9	991.93	41369.59	41522.83
Qwen-2.5-VL-72B	620.87	807.12	916.01	41252.15	41443.83
Claude-Sonnet-4	711.6	1007.23	1147.34	30370.33	30712.24
Seed-1-6-Thinking	641.62	834.78	934.9	40631.29	40826.14

Table 6: Average tokens consumption per video across all 200 samples of each model.

### A.3 Temperature Influence

We evaluate our approach using GPT-4o over using different temperatures in both the Claim and Multimodal settings. As shown in Table 7, performance fluctuations are slightly more pronounced in than multiple runs with temperature set to zero, yet these variations do not compromise the robustness of our conclusions.

GPT-4o	0.0	0.4	0.8	1.2	Mean $\pm$ Std
<i>Claim</i>					
False	63.3	59.3	56.7	62.0	60.3 $\pm$ 2.96
True	71.7	72.7	73.7	73.7	72.9 $\pm$ 0.96
All	67.5	66.0	65.2	67.8	66.6 $\pm$ 1.26
<i>Multimodal</i>					
False	44.7	44.3	47.3	41.7	44.5 $\pm$ 2.32
True	75.3	74.7	75.7	80.7	76.6 $\pm$ 2.75
All	60.0	59.5	61.5	61.2	60.5 $\pm$ 0.95

Table 7: Belief Scores (BS) of GPT-4o using the Claim and Multimodal settings with different temperatures.

### A.4 Inference Efficiency

To evaluate efficiency, we calculate the average token consumption (input & output) per video across all 200 samples using each model’s official tokenizer. The results (Table 6) reveal significant disparities in visual encoding efficiency. While text-based modalities (Claim, Transcript, OCR) consume fewer than 1.2k tokens on average, visual processing costs vary drastically. Notably, Gemini-2.5-Pro (our top-performing model) is highly efficient, using approximately 6.5k tokens for the Multimodal setting. In contrast, models like Qwen-VL-Max and Seed-1.6 require over 40k tokens for the same inputs.

### A.5 Ablation on All Modalities

The Multimodal setting specifically combines sampled video frames and audio transcripts. Since frames inherently contain visual representations of on-screen text, the explicit OCR-extracted textual sequences are not provided as a separate text input to avoid redundant textual prompting. To evaluate the impact of explicit on-screen text, we conduct additional experiments by incorporating OCR-extracted text into the Multimodal pipeline (Frame, Transcript, and Screen text).

The results are shown in Table 8. For some models (*e.g.*, GPT-4o, o3, Gemini-Flash), providing explicit OCR text leads to a notable improvement in the overall BS. For instance, GPT-4o’s overall score increases from 59.3 to 62.2. This confirms that supplemental textual information helps MLLMs better parse complex short-video content. We observe a distinct behavioral shift: most models show improved performance on the False subset but a slight decrease on the True subset, suggesting that explicit text makes models more sensitive to potential misinformation cues. Gemini-2.5-Pro is an exception, showing a more balanced integration with gains in the True subset.

Model	False	True	All
GPT-4o-20241120	52.3	72.0	62.2
o3-20250416	61.0	14.7	37.8
Gemini-2.5-Flash	74.3	60.3	67.3
Gemini-2.5-Pro	73.0	72.0	72.5
Claude-Sonnet-4	39.3	58.3	48.3

Table 8: Belief Scores (BS) of five models on false and true video subsets using the all Frame, ASR, and OCR.

## B More Results

Domain	N	Like	Share	Video Length (s)	Frame	Screen Text	Transcript
(1) Agri-Livestock & Fresh Produce	41	85,536 $\pm$ 224,724	31,406 $\pm$ 51,827	54.83 $\pm$ 49.94	20.88 $\pm$ 9.27	290.05 $\pm$ 288.29	225 $\pm$ 198.64
(2) Food Processing & Additives	44	34,264 $\pm$ 58,482	39,465 $\pm$ 82,430	54.90 $\pm$ 41.58	21.5 $\pm$ 10.02	312.68 $\pm$ 263.57	222.09 $\pm$ 198.64
(3) Chemicals, Appliances & Materials	37	45,277 $\pm$ 42,590	24,369 $\pm$ 22,276	55.10 $\pm$ 36.13	22.94 $\pm$ 8.37	326.35 $\pm$ 231.31	236.81 $\pm$ 168.27
(4) Health, Medical & Lifestyle	78	82,615 $\pm$ 167,045	93,649 $\pm$ 123,890	51.19 $\pm$ 33.22	21.78 $\pm$ 9.00	300.86 $\pm$ 200.58	231.23 $\pm$ 155.23
<b>All</b>	200	62,988 $\pm$ 173,236	51,676 $\pm$ 108,971	53.47 $\pm$ 39.26	21.8 $\pm$ 9.1	305.96 $\pm$ 238.98	228.98 $\pm$ 175.40

Table 9: Statistics of the videos shown in  $Mean \pm Std.$

Model	Agri-Livestock & Fresh Produce			Food Processing & Additives			Chemicals, Appliances & Materials			Health, Medical & Lifestyle		
	F	T	All	F	T	All	F	T	All	F	T	All
GPT-4o-20241120	29.7	55.0	42.3	39.7	<b>66.7</b>	53.2	18.3	68.3	43.3	60.3	79.7	70.0
o3-20250416	53.0	<u>18.3</u>	35.7	48.7	<u>1.7</u>	<u>25.2</u>	45.3	<u>18.3</u>	<u>31.8</u>	61.7	<u>29.7</u>	<u>45.7</u>
Gemini-2.5-Flash	62.0	46.0	54.0	65.7	41.7	53.7	50.7	46.3	48.5	<b>86.7</b>	58.0	72.3
Gemini-2.5-Pro	<b>66.3</b>	<b>71.0</b>	<b>68.7</b>	<b>76.0</b>	50.0	<b>63.0</b>	<b>67.3</b>	<b>71.3</b>	<b>69.3</b>	78.7	69.7	74.2
Qwen-VL-Max	42.3	49.0	45.7	52.0	40.0	46.0	60.7	43.7	52.2	59.7	71.0	65.3
Qwen-2.5-VL-72B	<u>16.3</u>	54.0	<u>35.2</u>	<u>22.7</u>	58.3	40.5	<u>3.7</u>	67.7	35.7	<u>37.3</u>	78.0	57.7
Claude-Sonnet-4	29.3	48.3	38.8	41.0	41.7	41.3	17.3	52.0	34.7	45.0	60.7	52.8
Seed-1.6-Thinking	54.0	61.7	57.8	60.7	61.7	61.2	23.3	58.7	41.0	72.7	<b>82.3</b>	<b>77.5</b>
<b>Average</b>	44.1	50.4	47.3	50.8	45.2	48.0	35.8	53.3	44.6	62.8	66.1	64.4

Table 10: Belief Scores (BS) of eight models across four domains on false and true video subsets using the *Claim* setting. **Bold** and Underlined values denote the best and worst performance per column, respectively.

Model	Unverified			Individual			Enterprise			Organization			w.o ID (All)		
	F	T	All	F	T	All	F	T	All	F	T	All	F	T	All
GPT-4o-20241120	72.0	77.7	74.8	38.0	63.3	50.7	52.0	71.7	61.8	<b>61.0</b>	76.0	<b>68.5</b>	63.3	71.7	67.5
o3-20250416	68.7	<u>38.3</u>	<u>53.5</u>	57.0	<u>43.7</u>	50.3	58.3	<u>57.7</u>	58.0	44.3	<u>46.3</u>	45.3	64.0	<u>46.3</u>	55.2
Gemini-2.5-Flash	81.3	<b>87.7</b>	84.5	78.7	47.0	62.8	81.3	<b>84.7</b>	<b>83.0</b>	<b>61.0</b>	59.3	60.2	79.7	70.0	74.8
Gemini-2.5-Pro	92.3	84.0	<b>88.2</b>	78.7	63.3	<b>71.0</b>	68.7	83.3	76.0	<b>61.0</b>	59.3	60.2	84.7	73.3	<b>79.0</b>
Qwen-VL-Max	<u>59.3</u>	55.7	57.5	33.3	46.0	39.7	50.0	75.7	62.8	<u>27.7</u>	61.0	44.3	52.3	59.0	55.7
Qwen-2.5-VL-72B	53.7	58.0	55.8	<u>26.3</u>	48.3	<u>37.3</u>	52.0	79.3	65.7	<u>27.7</u>	52.0	39.8	48.0	59.7	<u>53.8</u>
Claude-Sonnet-4	53.7	79.0	66.3	<u>26.3</u>	<b>69.0</b>	47.7	<u>46.0</u>	80.7	63.3	33.3	<b>79.7</b>	56.5	<u>47.3</u>	<b>76.7</b>	62.0
Seed-1.6-Thinking	<b>95.3</b>	49.3	72.3	<b>85.7</b>	53.0	69.3	<b>83.3</b>	77.0	80.2	<b>61.0</b>	57.3	59.2	<b>90.0</b>	59.0	74.5
<b>Average</b>	72.0	66.2	69.1	53.0	54.2	53.6	61.5	76.3	68.9	47.1	61.4	54.3	66.2	64.5	65.3

Table 11: Belief Scores (BS) of eight models across four channel verification statuses on false and true video subsets without channel IDs using the *Claim* setting. **Bold** and Underlined values denote the best and worst performance per column, respectively.

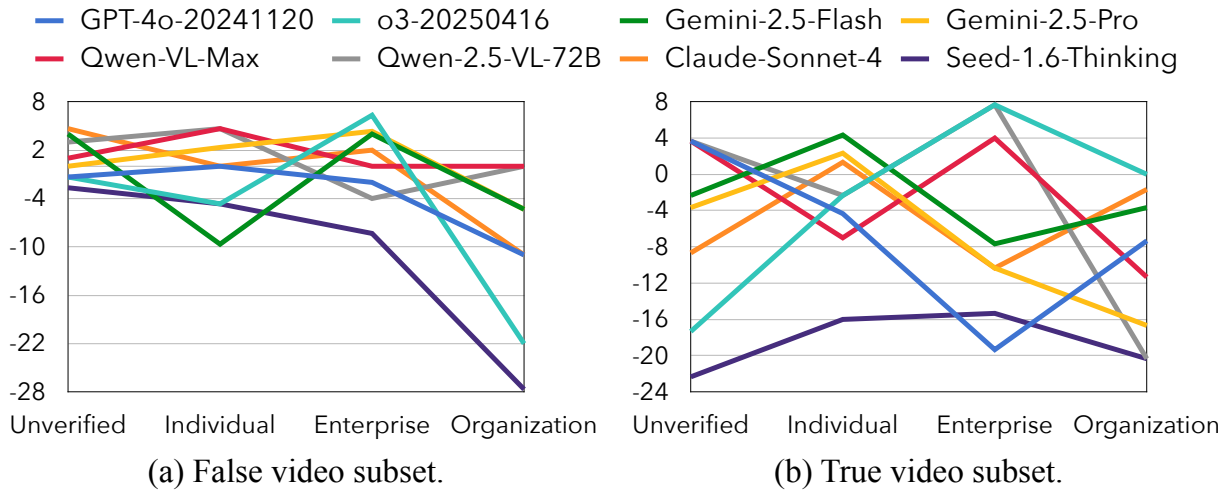


Figure 6: The difference ( $r_{\text{with\_ID}} - r_{\text{without\_ID}}$ ) rescaled by  $\frac{100}{3}$  across four verification statuses for eight models using the *Claim* setting on the false and true video subsets.

## C Prompts

### Modality: Claim

You are an expert fact-checker and your goal is to identify online misinformation. You will be provided with a claim extracted from a short video. Your task is to analyze it to determine if it is false beliefs or misinformation.

Here's how to approach the evaluation:

1. **Understand the Claim:** Carefully read and interpret the provided "Claim."
2. **Identify Core Assertions:** Break down the claim into its main assertions or factual statements.
3. **Cross-Reference and Verify:** Access your knowledge base to determine the veracity of each assertion. Consider:
  - \* Is this statement factually incorrect?
  - \* Does it contradict established scientific consensus, historical records, or widely accepted knowledge?
  - \* Is it presented out of context or in a misleading way?
  - \* Does it promote a conspiracy theory, pseudoscience, or harmful stereotype?
  - \* Is it an opinion disguised as a fact? (Note: Opinions themselves are not misinformation unless they are presented as verifiable facts and are demonstrably false).
4. Based on your analysis, provide a rating from 1 to 7 indicating your confidence about the presence of misinformation, where:
  - 1:** Very confident that the content has no misinformation
  - 2:** Confident that the content has no misinformation
  - 3:** Slightly confident that the content has no misinformation
  - 4:** Not at all confident that the content has/has no misinformation
  - 5:** Slightly confident that the content has misinformation
  - 6:** Confident that the content has misinformation
  - 7:** Very confident that the content has misinformation

Output must be in JSON format, containing two keys:

- \* **"Explanation"**: Your detailed reasoning for why the claim is or isn't misinformation, referencing specific elements of the claim and factual counterpoints if applicable.
- \* **"Rating"**: An integer between 1-7 reflecting your confidence about misinformation presence.

—  
Claim:  
[CLAIM]

Figure 7: The [CLAIM] is replaced by actual claim of each video.

**Modality: Textual**

You are an expert fact-checker and your goal is to identify online misinformation. You will be provided with text extracted from the screen of a short video using OCR. Your task is to analyze the provided content to determine if it contains false beliefs or misinformation.

Here's how to approach the task:

1. **Analyze the entire text carefully.** Look for claims, statements, or assertions that could be factually incorrect, misleading, or unsubstantiated.
2. **Identify specific points of potential misinformation.**
3. Explain **why** the points constitute misinformation. This explanation should reference common knowledge, widely accepted facts, or the logical inconsistencies within the provided text. If the information is accurate, explain why it is not misinformation.
4. Based on your analysis, provide a rating from 1 to 7 indicating your confidence about the presence of misinformation, where:
  - 1**: Very confident that the content has no misinformation
  - 2**: Confident that the content has no misinformation
  - 3**: Slightly confident that the content has no misinformation
  - 4**: Not at all confident that the content has/has no misinformation
  - 5**: Slightly confident that the content has misinformation
  - 6**: Confident that the content has misinformation
  - 7**: Very confident that the content has misinformation

Output must be in JSON format, containing two keys:

- \* **"Explanation"**: A detailed explanation of your reasoning, outlining specific false claims or confirming the accuracy of the information. If "Yes", clearly state what the misinformation is and why it's false. If "No", explain why the information is accurate.
- \* **"Rating"**: An integer between 1-7 reflecting your confidence about misinformation presence.

—  
Screen Text:

[TEXT]

Figure 8: The [TEXT] is replaced by actual textual text of each video.

**Modality: Aural**

You are an expert fact-checker and your goal is to identify online misinformation. You will be provided with transcript extracted from a short video. Your task is to analyze the provided content to determine if it contains false beliefs or misinformation.

Here's how to approach the task:

1. **Analyze the entire text carefully.** Look for claims, statements, or assertions that could be factually incorrect, misleading, or unsubstantiated.
2. **Identify specific points of potential misinformation.**
3. Explain **why** the points constitute misinformation. This explanation should reference common knowledge, widely accepted facts, or the logical inconsistencies within the provided text. If the information is accurate, explain why it is not misinformation.
4. Based on your analysis, provide a rating from 1 to 7 indicating your confidence about the presence of misinformation, where:
  - 1**: Very confident that the content has no misinformation
  - 2**: Confident that the content has no misinformation
  - 3**: Slightly confident that the content has no misinformation
  - 4**: Not at all confident that the content has/has no misinformation
  - 5**: Slightly confident that the content has misinformation
  - 6**: Confident that the content has misinformation
  - 7**: Very confident that the content has misinformation

Output must be in JSON format, containing two keys:

- \* **"Explanation"**: A detailed explanation of your reasoning, outlining specific false claims or confirming the accuracy of the information. If misinformation exists, clearly state what it is and why it's false. If accurate, explain why.
- \* **"Rating"**: An integer between 1-7 reflecting your confidence about misinformation presence.

—

Transcript:

[TRANSCRIPT]

Figure 9: The [TRANSCRIPT] is replaced by actual aural transcript of each video.

### Modality: Visual

You are an expert fact-checker and your goal is to identify online misinformation. You will be provided with several video frames in sequence extracted from a short video. Your task is to analyze the provided content to determine if it contains false beliefs or misinformation.

Here's how to approach the task:

1. **Analyze the entire frames carefully.** Look for claims, statements, assertions, or actions that could be factually incorrect, misleading, or unsubstantiated.
2. **Identify specific points of potential misinformation.**
3. Explain **why** the points constitute misinformation. This explanation should reference common knowledge, widely accepted facts, or the logical inconsistencies within the provided text. If the information is accurate, explain why it is not misinformation.
4. Based on your analysis, provide a rating from 1 to 7 indicating your confidence about the presence of misinformation, where:
  - 1**: Very confident that the content has no misinformation
  - 2**: Confident that the content has no misinformation
  - 3**: Slightly confident that the content has no misinformation
  - 4**: Not at all confident that the content has/has no misinformation
  - 5**: Slightly confident that the content has misinformation
  - 6**: Confident that the content has misinformation
  - 7**: Very confident that the content has misinformation

Output must be in JSON format, containing two keys:

- \* **"Explanation"**: A detailed explanation of your reasoning, outlining specific false claims or confirming the accuracy of the information. If "Yes", clearly state what the misinformation is and why it's false. If "No", explain why the information is accurate.
- \* **"Rating"**: An integer between 1-7 reflecting your confidence about misinformation presence.

Video frames:

[IMAGE]

Figure 10: The [IMAGE] is replaced by actual visual frames of each video.

### Modality: Multimodal

You are an expert fact-checker and your goal is to identify online misinformation. You will be provided with several video frames in sequence extracted from a short video and an associated audio transcript. Your task is to analyze the provided content to determine if it contains false beliefs or misinformation.

Here's how to approach the task:

1. **Analyze the entire frames carefully.** Look for claims, statements, assertions, or actions that could be factually incorrect, misleading, or unsubstantiated.
2. **Identify specific points of potential misinformation.**
3. Explain **why** the points constitute misinformation. This explanation should reference common knowledge, widely accepted facts, or the logical inconsistencies within the provided text. If the information is accurate, explain why it is not misinformation.
4. Based on your analysis, provide a rating from 1 to 7 indicating your confidence about the presence of misinformation, where:
  - 1**: Very confident that the content has no misinformation
  - 2**: Confident that the content has no misinformation
  - 3**: Slightly confident that the content has no misinformation
  - 4**: Not at all confident that the content has/has no misinformation
  - 5**: Slightly confident that the content has misinformation
  - 6**: Confident that the content has misinformation
  - 7**: Very confident that the content has misinformation

Output must be in JSON format, containing two keys:

- \* **"Explanation"**: A detailed explanation of your reasoning, outlining specific false claims or confirming the accuracy of the information. If "Yes", clearly state what the misinformation is and why it's false. If "No", explain why the information is accurate.
- \* **"Rating"**: An integer between 1-7 reflecting your confidence about misinformation presence.

Transcript: [TRANSCRIPT]

Video Frames: [IMAGE]

Figure 11: The [TRANSCRIPT] and [IMAGE] are replaced by actual aural transcripts and visual frames of each video.

### LLM-as-a-Judge

You are an expert in textual reasoning and logical analysis. You will receive a segment of CoT reasoning from an LLM, which explains how it determined whether a video contains misinformation. Additionally, you will receive the actual reason why the video contains misinformation. Based on the above requirements and your analysis, you need to determine whether the LLM's CoT reasoning includes this actual wrong reason and assign a rating of 1-4, where:

**\*\*1\*\***: LLM reasoning does not cover the actual wrong reason

**\*\*2\*\***: LLM reasoning covers a small part of the actual wrong reason

**\*\*3\*\***: LLM reasoning almost covers the actual wrong reason, but lacks some part

**\*\*4\*\***: LLM reasoning totally covers the actual wrong reason

Output must be in JSON format, containing two keys:

\* **"Explanation"**: A detailed explanation of your reasoning, outlining why you believe the LLM reasoning covers the actual wrong reason or not. If "Yes," explain the alignment; if "No," specify what is missing or incorrect.

\* **"Rating"**: An integer between 1-4 reflecting the extent to which the LLM reasoning covers the actual wrong reason.

——  
"LLM Reasoning": [REASONING]

"Wrong Reason": [REASON]

Figure 12: The [REASONING] and [REASON] are replaced by actual CoT output and the error reason for each video.

### Popularity Effect

[Original Claim or Multimodal Prompt]

—

[Corresponding Data Input]

This short video has received [A] views, [B] likes, [C] shares, and [D] comments.

Figure 13: The [Corresponding Data Input] is replaced by actual input data along with (views, likes, shares, comments) popularity statistics.

### Channel ID Effect

[Original Claim or Multimodal Prompt]

—

[Corresponding Data Input]

This short video was uploaded by [CHANNEL ID].

Figure 14: The [Corresponding Data Input] is replaced by actual input data along with [CHANNEL ID].