Format as a Prior: Quantifying and Analyzing Bias in LLMs for Heterogeneous Data

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Abstract

Large Language Models (LLMs) are increasingly employed in applications that require processing information from heterogeneous formats, including texts, tables, infoboxes, and knowledge graphs. However, systematic biases toward particular formats may undermine LLMs' ability to integrate heterogeneous data impartially, potentially resulting in reasoning errors and increased risks in downstream tasks. Yet it remains unclear *whether such biases are systematic*, *which data-level factors drive them*, and *what internal mechanisms underlie their emergence*.

In this paper, we present the first comprehensive study of format bias in LLMs through a three-stage empirical analysis. The first stage explores the presence and direction of bias across a diverse range of LLMs. The second stage examines how key data-level factors influence these biases. The third stage analyzes how format bias emerges within LLMs' attention patterns and evaluates a lightweight intervention to test its effectiveness. Our results show that format bias is consistent across model families, driven by information richness, structure quality, and representation type, and is closely associated with attention imbalance within the LLMs. Based on these investigations, we identify three future research directions to reduce format bias: enhancing data pre-processing through format repair and normalization, introducing inference-time interventions such as attention reweighting, and developing format-balanced training corpora. These directions will support the design of more robust and fair heterogeneous data processing systems.

Code — https://github.com/NLPGM/Format-as-a-prior

Appendix — https://github.com/NLPGM/Format-as-a-prior/appendix.pdf

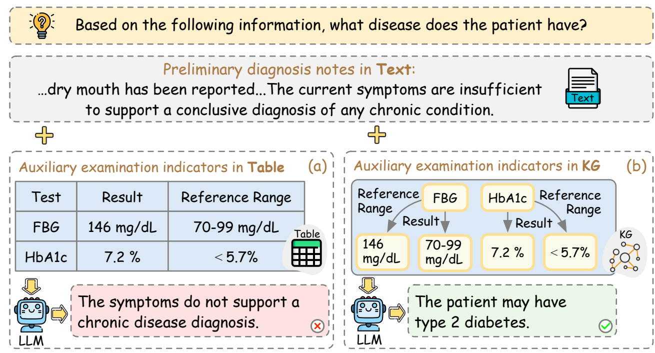

Figure 1: Format bias affects the LLM's decision.

1 Introduction

Large Language Models (LLMs) have demonstrated impressive capabilities across a wide range of natural language tasks (Brown et al. 2020). However, their practical deployment remains constrained by key limitations, including factual inaccuracies (commonly referred to as "hallucinations") (Ji et al. 2023) and incomplete or outdated knowledge (Petroni et al. 2019). One promising direction to address these issues is to incorporate external knowledge sources into the reasoning process—allowing models to ground their outputs in more accurate, up-to-date, and contextually relevant information (Lewis et al. 2020; Gao et al. 2023; Huang and Chang 2022).

In practice, external knowledge exists in diverse formats, ranging from unstructured texts to semi-structured infoboxes, as well as structured tables and Knowledge Graphs (KGs). These different sources of knowledge often complement one another, and the ability to effectively harness them together is crucial for real-world, knowledge-intensive applications.

The presence of different formats introduces a critical challenge: LLMs may not treat all formats equally when leveraging these heterogeneous data collaboratively. An LLM with strong format preferences interprets information through a distorted lens, giving undue weight to favored formats regardless of actual relevance. This can affect its ability to reason and synthesize effectively.

For example, in clinical decision support, an LLM (e.g., Qwen3-8b) given both textual notes and tabular examination data may overemphasize the text while overlooking key indicators in the table, leading to an incorrect diagnosis. In contrast, as shown in Figure 1, presenting the same information in a knowledge graph enables the model to identify abnormalities and reach the correct conclusion.

When homogeneous inputs are converted into hetero-

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geneous ones with equivalent content, accuracy decreases by 9% and 12% on HotpotQA (Yang et al. 2018) and MuSiQue (Trivedi et al. 2022) (200 samples each), confirming that format heterogeneity can directly impair reasoning performance. This phenomenon may widely arise in heterogeneous reasoning (Christmann, Saha Roy, and Weikum 2024), where key evidence is distributed across texts, tables, infoboxes, and knowledge graphs. LLMs may focus on information from their preferred formats, potentially overlooking crucial data in others. Such bias can result in incomplete or flawed conclusions and undermine the LLMs' role as impartial and effective synthesizers of heterogeneous inputs.

Although there have been several studies exploring various types of bias in LLMs, such as bias between multi-modal data (Zhu et al. 2024; Zhang et al. 2025), there is a lack of systematic research on format bias. To address this gap, we present the first comprehensive investigation and analysis of format bias in LLMs. Our study centers on three critical questions: *whether such format biases are systematic*, *which data-level factors contribute to them*, and *what internal mechanisms in LLMs underlie their emergence*.

To systematically investigate the three questions, we conduct a three-stage empirical study by constructing a heterogeneous data conflict scenario for the exploration of bias. The first stage explores the presence and direction of bias across a diverse range of LLMs. The second stage aims to examine how key data-level factors, including information richness, structure quality, and format type, influence these biases. The third stage investigates the emergence of format bias within LLMs' attention mechanisms and evaluates a lightweight intervention strategy to assess its effectiveness in mitigating such bias.

Our results reveal that format bias is both systematic and consistent across models, driven primarily by differences in information richness, structure quality, and format type. We further show that such bias originates from imbalanced attention allocation during inference and can be partially mitigated through attention-based interventions.

Our key contributions are as follows:

1. To the best of our knowledge, we are the first to investigate the issue of format bias in LLMs and to present a comprehensive investigation of LLM biases toward different knowledge formats across a wide range of LLMs.
2. We conduct a three-stage empirical study to examine the presence and direction of bias, identify the data-level factors that give rise to the bias, and investigate the internal mechanisms in LLMs that contribute to their presence.
3. Based on the comprehensive investigation, we identify three future research directions that may reduce the format bias, which will contribute the development of a more effective heterogeneous data processing system.

2 Related Work

2.1 Heterogeneous reasoning

An important direction in AI research is to develop LLMs capable of reasoning over heterogeneous knowledge sources, including unstructured texts, tables, and KGs, especially when relevant evidence is dispersed across different formats. However, existing methods often struggle to integrate such fragmented information effectively for accurate inference.

To formalize this challenge, recent benchmarks such as *COMPMIX* (Christmann, Saha Roy, and Weikum 2024) and *CompMix-IR* (Min et al. 2024) require cross-format reasoning, stimulating the development of hybrid QA systems that combine structured and unstructured inputs.

Current approaches can be broadly categorized into two types: (1) *Unified retrieval frameworks*, which abstract away format heterogeneity using shared APIs or embedding spaces (Xia et al. 2025; Min et al. 2024); and (2) *LLM-centric pipelines*, which enhance downstream reasoning via evidence selection, re-ranking, or modular tool use (Christmann and Weikum 2024; Lehmann et al. 2024; Zhang et al. 2024; Biswal et al. 2024).

However, existing work often assumes that once evidence is retrieved, LLMs will evaluate it fairly based on content alone. Our study revisits this assumption by asking whether the format in which evidence is presented can influence the model's judgment, even when the underlying meaning remains the same.

2.2 LLM Behavior under Conflicting Evidence

Recent studies have uncovered a broad range of behavioral biases in LLMs, extending beyond social stereotypes to systematic patterns in reasoning and judgment. A key challenge lies in how LLMs handle conflicts—both between their *parametric knowledge* (internal beliefs) and *in-context evidence*, and among competing pieces of evidence (Xu et al. 2024). LLMs tend to favor information aligned with their pre-trained knowledge, even when contradicted by accurate inputs (Jin et al. 2024a; Xie et al. 2023). These LLM biases are shaped by factors such as entity popularity (Xie et al. 2023), event recency (Fang et al. 2023), and evidence frequency (Jin et al. 2024a). Input artifacts also affect LLM behavior, such as preferring self-generated content over retrieved passages (Tan et al. 2024). Related efforts have also examined knowledge conflicts in multi-modal (Zhang et al. 2025; Zhu et al. 2024) and multi-agent settings (Ju et al. 2025), where preference biases and inter-agent inconsistency further complicate reasoning.

Benchmarks like *ConflictBank* (Su et al. 2024), *WikiContradict* (Hou et al. 2024), and *WhoQA* (Pham et al. 2024) have been proposed to evaluate how LLMs handle factual or semantic inconsistencies, especially in ambiguous scenarios. In response, a range of strategies have emerged, including conflict-aware decoding (Yuan et al. 2024; Jin et al. 2024a), counterfactual data augmentation (Fang et al. 2023), internal intervention via attention pruning (Jin et al. 2024b), neuron reweighting (Shi et al. 2024), or prompting LLMs to generate multi-answer responses with source attribution (Shaier, Kobren, and Ogren 2024).

Our work extends prior research by identifying a previously overlooked source of bias: the format in which information is presented. In contrast to earlier studies that focus on content-level factors such as recency or frequency, we

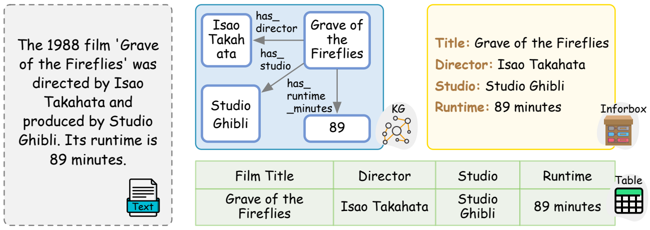

Figure 2: Examples of the four data formats used in our experiments: texts, tables, infoboxes, and KGs.

show that differences in format representation alone can systematically influence LLMs' behavior.

3 Investigation Framework

This section establishes a framework for analyzing format bias in LLMs, encompassing dataset construction, confounding factor exclusion, and automated response evaluation. The dataset construction process is detailed in Appendix A, with evaluation details in Appendix B.

3.1 Dataset and Format Construction

We construct our dataset based on *ConflictBank* (Su et al. 2024), a public corpus designed to evaluate LLM behavior under factual conflicts. We randomly sample 4,000 entries, each containing one factual claim and three counterclaims with corresponding supporting evidence. This results in 12,000 contradiction pairs, as each claim is paired individually with each of the three counterclaims. Each pair consists of two different claims about the same subject and relation, each supported by its own piece of evidence.

While the original evidence in *ConflictBank* is presented in plain text, our goal is to examine how LLM behavior is influenced by presenting supporting evidence in different data formats. To construct each heterogeneous contradiction pair, we randomly convert the two pieces of evidence, each of which supports a different claim about the same subject, into different formats. If the selected format is text, no conversion is applied.

We use GPT-4o-mini as a transformation engine to convert selected texts into one of the following Wikipedia-inspired formats.

- KGs: A set of (Subject, Predicate, Object) triples capturing core semantic relations.
- Infobox: A structured key-value format modeled after Wikipedia infobox templates, summarizing factual information.
- Table: A tabular format styled after Wikipedia tables, presenting comparable facts in labeled rows and columns.

Figure 2 provides illustrative examples of these four formats, showing how semantically equivalent information can be presented in structurally distinct ways. These formats reflect the most commonly used representations in prior work on heterogeneous reasoning. Manual inspection of 5% samples confirms 98.7% factual and 99.3% syntactic accuracy, reflecting strong data fidelity.

3.2 Confounding Factor Control

To ensure that our evaluation isolates the effect of evidence format itself, we implement controls to eliminate two major confounding factors: internal knowledge bias and evidence presentation order.

- Filtering Internal Knowledge: To ensure that LLM responses are based on external evidence rather than parametric memory, we adopt a filtering procedure consistent with prior work (Gekhman et al. 2024). Each factual claim is tested 16 times by directly querying a given LLM with the corresponding question in a zero-shot setting, and only those samples for which the model fails to reproduce the factual claim in all trials are retained.
- Randomizing Evidence Order: To eliminate the known bias introduced by input order (Xie et al. 2023), we randomize the sequence of all evidence segments for each input.

3.3 Evaluated LLMs

This evaluation covers ten LLMs across six major series: GPT-4o-mini (Achiam et al. 2023), LLaMA-3.1 (8B), Mistral (7B), Qwen3 (8B, 14B, 30B-A3B, 32B) (Team 2025), Gemma-2 (9B, 27B) (Team et al. 2024), and GLM-4 (9B) (GLM et al. 2024). These LLMs span a range of sizes and architectures, enabling cross-family comparison of format-driven biases.

To ensure reproducibility and eliminate stochasticity, all evaluations were conducted in deterministic inference mode (temperature = 0, without sampling randomness).

3.4 Evaluation Protocol and Metrics

Given the dataset's scale, we adopt an automated evaluation pipeline using LLMs as adjudicators. Specifically, GPT-4o-mini, GLM-4.5-Air (Zeng et al. 2025), and Qwen-plus are employed to judge which of the two conflicting claims (Source A or Source B) each target response supports.

Each model independently evaluates every sample three times for stability, with the final label per model determined by majority vote. We then compute FPR and DCR for each model and report their averages across the three evaluators. This multi-model setup improves consistency and mitigates variance in individual LLM judgments. Manual checks on a randomly sampled 5% subset show 99.8% agreement between human and averaged LLM judgments, confirming high reliability.

Each LLM response is classified into one of three mutually exclusive categories:

- **Pref-A:** The response predominantly or exclusively supports the claim from Source A.
- **Pref-B:** The response predominantly or exclusively supports the claim from Source B.
- **Both:** The response acknowledges the contradiction and presents both perspectives in a comparative or side-by-side manner.

All responses in our experiments fall unambiguously into one of these three categories, and no additional response types are observed. This categorization enables two quantitative bias metrics used throughout our analysis.:

- **Dual Coverage Rate (DCR)**: Measures the proportion of responses that acknowledge both claims, indicating an LLM's capacity to represent multiple perspectives:

$$\mathrm{DCR} = \frac{\text{Both}}{\text{Pref-A} + \text{Pref-B} + \text{Both}} \tag{1}$$

- **Format Preference Ratio (FPR)**: Captures asymmetric bias between conflicting claims when an LLM gives a single-sided response. For the A vs. B experiments, the FPR is calculated as:

$$\mathrm{FPR} = \frac{\text{Pref-A}}{\text{Pref-A} + \text{Pref-B}} \tag{2}$$

These two metrics correspond to the two bias types introduced earlier: **DCR** captures the presence of bias, while **FPR** captures the direction of bias.

4 Experimental Results and Analysis

In this section, we present the empirical results of our three-stage investigation. Complete experimental details and raw results are provided in Appendix C.

4.1 Establishing the Existence of Format Bias

Objective and Setup The primary aim of this initial experiment is to test the null hypothesis that LLMs process information in a format-agnostic manner. To this end, we conduct a large-scale evaluation using the experimental framework outlined in Section 3. We assess ten state-of-the-art LLMs from various families and parameter scales. Each LLM is evaluated on all six possible pairs among the four target data formats: texts, tables, infoboxes, and KGs. This design yields 60 unique experimental conditions (10 LLMs $\times$ 6 format pairs), enabling a comprehensive assessment of systematic format biases.

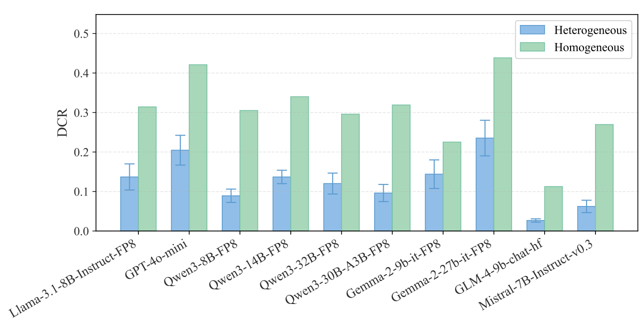

Figure 3: Average DCR across models under heterogeneous and homogeneous formats. Error bars show standard error.

Top-Level Findings Our results provide strong evidence against the null hypothesis of format impartiality, revealing instead a consistent and multifaceted pattern of bias in both its presence and direction.

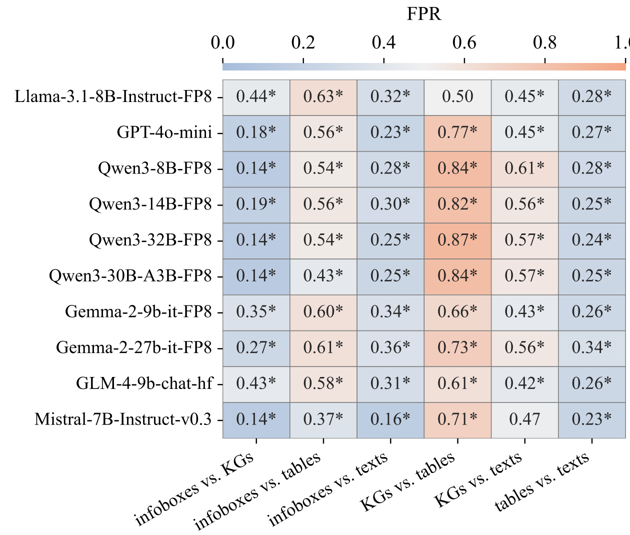

Figure 4: Heatmap of FPR between format pairs across LLMs. Asterisks (*) indicate statistical significance under a two-sided binomial test with null hypothesis FPR $= 0.5$.

The first pattern, the presence of bias, is pervasive under heterogeneous format conditions. This is reflected in the uniformly low Dual Coverage Rate (DCR), ranging from 3.01% to 24.02%, indicating that LLMs often fail to acknowledge conflicting information across different formats, typically exhibiting a preference for one input while disregarding the other.

To isolate the role of format, we introduce a control condition where both inputs are presented in plain text. As shown in Figure 3, DCR increases markedly under this homogeneous setting. This contrast highlights a broader pattern: format heterogeneity alone can independently and substantially impair a model's ability to jointly consider multiple inputs, even when the content is semantically equivalent.

This limitation persists across models of varying size, as no clear scaling trend is observed. For example, within the Qwen3 series, larger models do not exhibit improved performance in this regard, suggesting that increased parameter size alone does not resolve this form of processing asymmetry.

The second, and more decisive, pattern is a strong directional bias that emerges when an LLM commits to a single-sided response. Despite considerable variation in architecture and scale, LLMs demonstrate a surprisingly consistent pattern of format preferences. As shown in Figure 4, our cross-model analysis reveals a clear preference hierarchy: semantically rich formats such as texts and KGs are consistently favored over visually structured ones like infoboxes and tables. Furthermore, when we group the data by topical domain, we find that these biases persist across domains, suggesting that the observed biases are robust and generalizable. See Appendix C.7 for detailed domain-level results.

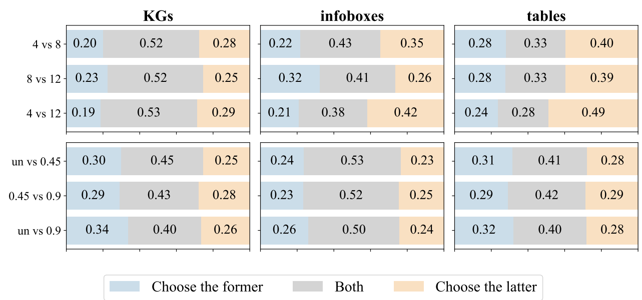

Figure 5: LLM biases across conditions (averaged over ten LLMs). Top: Information Richness; Bottom: Structure Quality. Bars show the proportion of responses favoring the former input, the latter, or both.

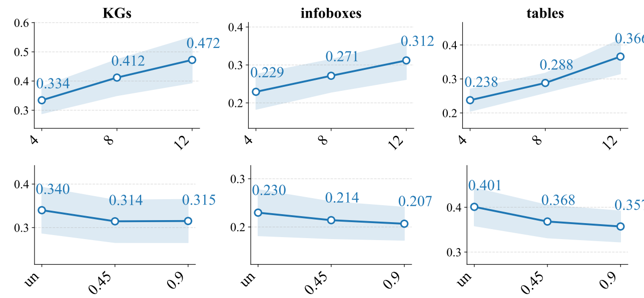

Figure 6: Average FPR for structured data vs. texts across ten LLMs. Top: Information Richness; Bottom: Structure Quality. Shaded areas indicate mean ± one standard deviation.

4.2 Identifying the Factors Behind Format Bias

Having established the widespread presence of format bias, we now turn to investigating its data-level factors. While prior work has extensively explored factors influencing LLM biases in textual inputs, our focus is on structured data and the properties that may shape LLM behavior in this context. To move from identifying whether such bias exists to understanding why it arises, we decompose the abstract notion of "format" into three representative and controllable dimensions: the structure itself, and the content, which we further divide into quantity and quality.

Building on this decomposition, we hypothesize that three key dimensions (the amount of information conveyed, referred to as quantity; the structural quality of that information, or quality; and the mode of presentation, or format type) play a central role in shaping how LLMs evaluate evidence.

To assess the influence of these factors, we design a unified experimental framework that applies to two of the three factors (with the exception of the format type). Each of these two factors is examined under two complementary conditions:

- **Homogeneous setting**: Two evidence sources of the same format are compared, differing only in the factor under investigation. This controlled design isolates the variable to reveal an LLM's intrinsic sensitivity to that property.
- **Heterogeneous setting**: A structured evidence source is paired with unstructured plain texts. This setup assesses the relative strength of the structured format and how its properties influence an LLM's preference when compared against a universal baseline.

Factor 1: Information Richness This factor concerns the volume of factual detail within an external knowledge source used during reasoning. In real-world applications, the external context provided to LLMs often varies widely in the amount of information it contains. It serves as a proxy for the completeness of factual detail. To examine whether LLMs apply a "more is better" heuristic, interpreting quantity as indicative of evidentiary strength, we systematically vary the number of entries in structured formats (e.g., table rows or knowledge graph triples).

In the homogeneous setting, we conduct experiments within each format type (tables, KGs, and infoboxes), comparing three levels of information richness across three pairwise conditions: 4 vs. 8 entries, 8 vs. 12 entries, and 4 vs. 12 entries.Results consistently indicate that LLMs favor the richer variant in each pair, irrespective of format. This suggests that even when structure is held constant, LLMs exhibit a systematic bias for inputs with more factual content (see Figure 5).

In the heterogeneous setting, we assess whether this preference generalizes when structured inputs are compared against unstructured texts. For each format, we construct three pairs: texts vs. 4-entry structure, texts vs. 8-entry structure, and texts vs. 12-entry structure. All structured inputs are generated from the same source texts as the corresponding text versions, ensuring content consistency. Across all formats, LLMs' bias for the structured inputs increases with the number of entries (see Figure 6).

These findings suggest that LLMs tend to associate greater volumes of factual content with higher evidentiary value, both within individual formats and when comparing structured and unstructured inputs.

Factor 2: Structure Quality This factor examines whether LLMs are sensitive to the structural integrity of external knowledge inputs. In practice, structured formats like tables or knowledge graphs may contain noise or malformed syntax. To simulate this, we introduce controlled corruption into structure-defining tokens (e.g., brackets, colons, separators), randomly replacing them with other characters or blanks at fixed probabilities (0.45 and 0.9), while preserving the underlying factual content.

In the homogeneous setting, we compare clean and corrupted versions within each format type. LLMs consistently favor the well-formed input, confirming that structure quality serves as a reliability signal. Notably, the preference saturates beyond moderate corruption (e.g., 0.45), indicating that LLMs tend to treat inputs as either structurally valid or invalid (see Figure 5).

In the heterogeneous setting, we pair each corrupted version with its corresponding clean texts. Each corruption level is applied to the same intact structured data instance, guaranteeing that the underlying information remains identical across differently corrupted versions. LLMs' bias for the structured inputs declines sharply as corruption increases, despite identical semantics. This suggests that structural degradation alone can undermine the perceived credibility of otherwise accurate structured inputs (see Figure 6).

Factor 3: Format Type This factor investigates the impact of the representational structure and layout used to represent logically equivalent information. The choice between plain text, a relational graph (KGs), or a visual grid (tables, infoboxes) embodies core differences in format semantics. Holding the content constant, we ask: do LLMs possess intrinsic preferences for certain data structures?

Metric	Infobox	Table	KGs
FPR	0.235	0.398	0.336

Table 1: Average FPR between structured data and texts (mean across ten LLMs).

We construct matched pairs with identical factual entries in both texts and structured variants. As shown in Table 1, the results reveal a consistent hierarchy: tables are most competitive, followed by KGs, with infoboxes least preferred. All three structured variants contain nearly identical content, differing only in their representational layout. This suggests that the format itself, rather than the informational content, modulates LLMs' bias.

Cross-Factor Insight Consistent with the findings in Section 4.1, we observe that format homogeneity substantially reduces bias in presence. This trend holds not only for unstructured inputs but also extends to structured formats such as tables and knowledge graphs, where DCR increases significantly (28%–53%) when both inputs adopt the same format. These results suggest that LLMs are more capable of jointly considering multiple sources of information when they are presented in a uniform structure. In contrast, even when the content is semantically equivalent, presenting information in heterogeneous formats tends to impair integration and leads to partial or selective processing.

4.3 Mechanism Behind Format Bias

In this analysis, we move beyond identifying data-level factors to analyzing how format bias manifests within the internal processing of LLMs. Our aim is to examine whether differences in attention allocation across input formats are associated with the presence and direction of bias identified earlier. We focus our analysis on three representative LLMs from different model families: Qwen3-8B, Mistral-7B-Instruct-v0.3, and Llama-3.1-8B-Instruct.

The Relation Between Attention Allocation and Presence of Bias We begin by analyzing how attention is distributed between conflicting evidence inputs during inference. For each input pair, we compute the mean attention mass assigned to each segment and then calculate the absolute difference between the two values to quantify the degree of imbalance.

To quantify the negative correlation between attention gap and DCR, we employ Spearman's rank correlation coefficient as a measurement. The results show coefficients of –0.31, –0.37, and –0.54 across the three LLMs, indicating a weak to moderate negative correlation. This suggests that greater imbalance in attention distribution is associated with a lower likelihood of the model recognizing both sources of information.

This implies that format bias arises, at least in part, from skewed attention allocation early in processing, which increases the chance of one source being overlooked.

The Relation Between Attention Allocation and Direction of Bias We further examine whether attention allocation can explain which input LLMs tend to prefer when selecting only one side. Interestingly, in 82.35 percent of such cases, they favor the source that received less attention.

This observation implies that while attention imbalance affects whether both sources are represented in the output, it does not consistently determine the direction of preference. In other words, a segment receiving more attention does not necessarily have a higher chance of being selected as the final answer.

These results indicate that attention allocation is related to both types of bias, though the nature of this relationship may differ.

Attention-Guided Intervention To move from correlation to causation, we design an intervention that directly modifies the internal representations produced by the attention mechanism.

Specifically, we apply a normalization-based reweighting to the attention distribution at each generation step. Let $A \in \mathbb{R}^{H \times L_q \times L_k}$ denote the attention tensor, where H is the number of heads, L_q the query sequence length, and L_k the key sequence length. At the current decoding step, we denote the attention distribution over keys as $a \in \mathbb{R}^{L_k}$, where a_j represents the attention weight assigned to the j-th key token.

To ensure that the two pieces of evidence receive equal total attention, we define the corresponding token index sets I_1 and I_2, and compute the total attention mass on each:

$$m_1 = \sum_{j \in I_1} a_j, \quad m_2 = \sum_{j \in I_2} a_j \tag{3}$$

We then compute their average:

$$\bar{m} = \frac{m_1 + m_2 + \varepsilon}{2} \tag{4}$$

where ε is a small constant for numerical stability. The attention weights are reweighted accordingly:

$$a'_j = \begin{cases} \frac{\bar{m}}{m_1+\varepsilon} \cdot a_j, & j \in I_1 \\ \frac{\bar{m}}{m_2+\varepsilon} \cdot a_j, & j \in I_2 \\ a_j, & \text{otherwise} \end{cases} \tag{5}$$

This procedure enforces equal total attention mass across the two evidence segments, while preserving the original intra-segment distribution.

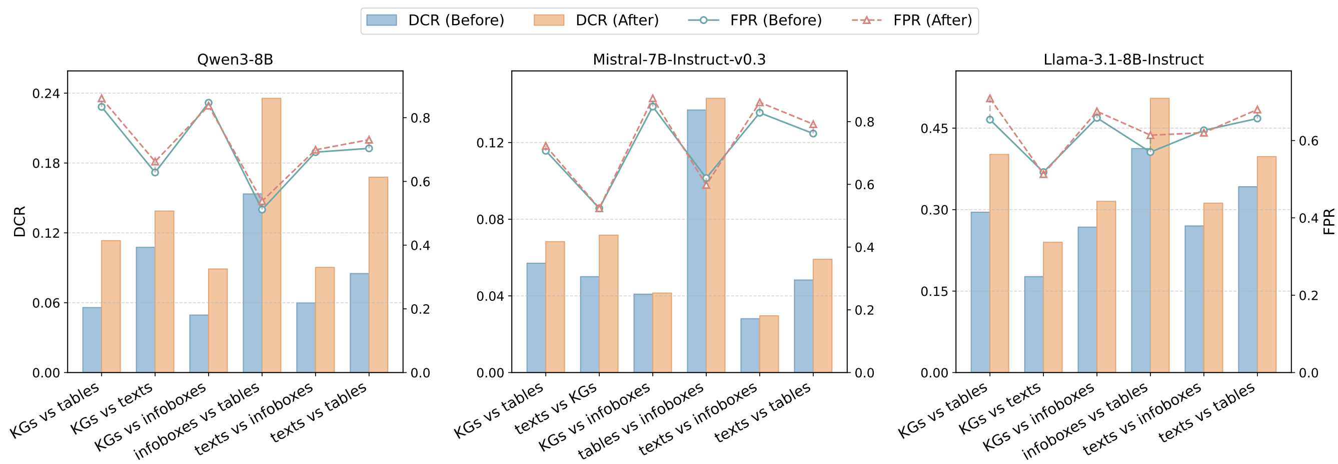

Figure 7: Effects of intervention methods in terms of DCR and FPR.

Experiment Results We apply the attention-balancing intervention to three representative LLMs and compare their behavior before and after modification.

The results reveal a consistent improvement in the models' ability to attend to both conflicting sources: DCR significantly increases across all format pairs and all three models (see Figure 7). This suggests that enforcing a more balanced attention distribution during inference effectively encourages the model to integrate information from both input segments, rather than overlooking one entirely. When applied to heterogeneous-input reasoning tasks, the attention-balancing method also improves performance on downstream RAG-style QA datasets, including HotpotQA and MuSiQue, where accuracy increases by 6.5% and 9.5%, respectively.

In contrast, FPR remains largely stable after the intervention, and the changes are not statistically significant across the evaluated models (see Figure 7). This implies that although the LLMs process both sources more evenly, the intervention has limited effect on their final output preferences once a directional bias has emerged.

The different effects of attention interventions on DCR and FPR suggest that presence of biases are at least partially controllable at inference time, whereas direction of biases are more resistant to modification. These more stable preferences may reflect deeper inductive biases acquired during pretraining, such as stronger alignment with textual inputs.

5 Discussion

Our findings show that format bias in LLMs is systematic and has practical consequences for systems processing heterogeneous data. To mitigate it, interventions can be applied at three levels: pre-processing, inference, and model development.

Data Pre-processing Pre-processing is a cost-effective way to reduce bias. Since LLMs tend to trust well-structured inputs, automatically repairing corrupted format in tables or KGs can prevent valuable content from being dismissed. Additionally, using a consistent input format can help reduce format-induced bias, as LLMs perform better when differences in input format is minimized. During the transformation process, it is important to preserve all essential information while avoiding the introduction of noise or unintended alterations.

Inference-Time Intervention Re-balancing attention across inputs during inference can help LLMs more effectively integrate information from multiple sources, reducing the tendency to overlook less-preferred formats. By encouraging the model to distribute attention more evenly across heterogeneous data, it enhances the model's ability to incorporate information from all inputs and supports more robust and balanced reasoning. Although such adjustments may not fully shift the model's final output bias, they improve its intermediate processing. Future work may explore more fine-grained or deeper intervention strategies to better align model attention with content relevance and reduce structural bias during inference.

Model Development and Fine-tuning Format preferences likely originate from pretraining data imbalance. Mitigation may involve training on format-balanced corpora, using contrastive objectives, or incorporating format-aware modules. Though costlier than inference-time methods, such approaches offer a more fundamental solution.

6 Conclusion

This work presents the first in-depth study of format bias in LLMs, identifying it as a consistent effect driven by information richness, structure quality, and format type. The bias manifests in two types: the presence of bias that can be mitigated, and the direction of bias likely rooted in pretraining. These findings underscore the importance of treating data format as a core factor in LLM design and evaluation. We also outline practical mitigation strategies, including data preprocessing, inference-time attention adjustment, and format-aware training, which together offer clear paths for reducing format bias in heterogeneous reasoning.

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References

Achiam, J.; Adler, S.; Agarwal, S.; Ahmad, L.; Akkaya, I.; Aleman, F. L.; Almeida, D.; Altenschmidt, J.; Altman, S.; Anadkat, S.; et al. 2023. Gpt-4 technical report. *arXiv preprint arXiv:2303.08774*.

Biswal, A.; Patel, L.; Jha, S.; Kamsetty, A.; Liu, S.; Gonzalez, J. E.; Guestrin, C.; and Zaharia, M. 2024. Text2sql is not enough: Unifying ai and databases with tag. *arXiv preprint arXiv:2408.14717*.

Brown, T.; Mann, B.; Ryder, N.; Subbiah, M.; Kaplan, J. D.; Dhariwal, P.; Neelakantan, A.; Shyam, P.; Sastry, G.; Askell, A.; et al. 2020. Language models are few-shot learners. *Advances in neural information processing systems*, 33: 1877–1901.

Christmann, P.; Saha Roy, R.; and Weikum, G. 2024. Compmix: A benchmark for heterogeneous question answering. In *Companion Proceedings of the ACM Web Conference 2024*, 1091–1094.

Christmann, P.; and Weikum, G. 2024. Rag-based question answering over heterogeneous data and text. *arXiv preprint arXiv:2412.07420*.

Fang, T.; Wang, Z.; Zhou, W.; Zhang, H.; Song, Y.; and Chen, M. 2023. Getting sick after seeing a doctor? diagnosing and mitigating knowledge conflicts in event temporal reasoning. *arXiv preprint arXiv:2305.14970*.

Gao, Y.; Xiong, Y.; Gao, X.; Jia, K.; Pan, J.; Bi, Y.; Dai, Y.; Sun, J.; Wang, H.; and Wang, H. 2023. Retrieval-augmented generation for large language models: A survey. *arXiv preprint arXiv:2312.10997*, 2(1).

Gekhman, Z.; Yona, G.; Aharoni, R.; Eyal, M.; Feder, A.; Reichart, R.; and Herzig, J. 2024. Does fine-tuning LLMs on new knowledge encourage hallucinations? *arXiv preprint arXiv:2405.05904*.

GLM, T.; :; Zeng, A.; Xu, B.; Wang, B.; Zhang, C.; Yin, D.; Zhang, D.; Rojas, D.; Feng, G.; Zhao, H.; Lai, H.; Yu, H.; Wang, H.; Sun, J.; Zhang, J.; Cheng, J.; Gui, J.; Tang, J.; Zhang, J.; Sun, J.; Li, J.; Zhao, L.; Wu, L.; Zhong, L.; Liu, M.; Huang, M.; Zhang, P.; Zheng, Q.; Lu, R.; Duan, S.; Zhang, S.; Cao, S.; Yang, S.; Tam, W. L.; Zhao, W.; Liu, X.; Xia, X.; Zhang, X.; Gu, X.; Lv, X.; Liu, X.; Liu, X.; Yang, X.; Song, X.; Zhang, X.; An, Y.; Xu, Y.; Niu, Y.; Yang, Y.; Li, Y.; Bai, Y.; Dong, Y.; Qi, Z.; Wang, Z.; Yang, Z.; Du, Z.; Hou, Z.; and Wang, Z. 2024. ChatGLM: A Family of Large Language Models from GLM-130B to GLM-4 All Tools. arXiv:2406.12793.

Hou, Y.; Pascale, A.; Carnerero-Cano, J.; Tchrakian, T.; Marinescu, R.; Daly, E.; Padhi, I.; and Sattigeri, P. 2024. Wikicontradict: A benchmark for evaluating llms on real-world knowledge conflicts from wikipedia. *Advances in Neural Information Processing Systems*, 37: 109701–109747.

Huang, J.; and Chang, K. C.-C. 2022. Towards reasoning in large language models: A survey. *arXiv preprint arXiv:2212.10403*.

Ji, Z.; Lee, N.; Frieske, R.; Yu, T.; Su, D.; Xu, Y.; Ishii, E.; Bang, Y. J.; Madotto, A.; and Fung, P. 2023. Survey of hallucination in natural language generation. *ACM computing surveys*, 55(12): 1–38.

Jin, Z.; Cao, P.; Chen, Y.; Liu, K.; Jiang, X.; Xu, J.; Li, Q.; and Zhao, J. 2024a. Tug-of-war between knowledge: Exploring and resolving knowledge conflicts in retrieval-augmented language models. *arXiv preprint arXiv:2402.14409*.

Jin, Z.; Cao, P.; Yuan, H.; Chen, Y.; Xu, J.; Li, H.; Jiang, X.; Liu, K.; and Zhao, J. 2024b. Cutting off the head ends the conflict: A mechanism for interpreting and mitigating knowledge conflicts in language models. *arXiv preprint arXiv:2402.18154*.

Ju, T.; Wang, B.; Fei, H.; Lee, M.-L.; Hsu, W.; Li, Y.; Wang, Q.; Cheng, P.; Wu, Z.; Zhang, Z.; et al. 2025. Investigating the Adaptive Robustness with Knowledge Conflicts in LLM-based Multi-Agent Systems. *arXiv preprint arXiv:2502.15153*.

Lehmann, J.; Bhandiwad, D.; Gattogi, P.; and Vahdati, S. 2024. Beyond boundaries: A human-like approach for question answering over structured and unstructured information sources. *Transactions of the Association for Computational Linguistics*, 12: 786–802.

Lewis, P.; Perez, E.; Piktus, A.; Petroni, F.; Karpukhin, V.; Goyal, N.; Küttler, H.; Lewis, M.; Yih, W.-t.; Rocktäschel, T.; et al. 2020. Retrieval-augmented generation for knowledge-intensive nlp tasks. *Advances in neural information processing systems*, 33: 9459–9474.

Min, D.; Xu, Z.; Qi, G.; Huang, L.; and You, C. 2024. UniHGKR: Unified Instruction-aware Heterogeneous Knowledge Retrievers. *arXiv preprint arXiv:2410.20163*.

Petroni, F.; Rocktäschel, T.; Lewis, P.; Bakhtin, A.; Wu, Y.; Miller, A. H.; and Riedel, S. 2019. Language models as knowledge bases? *arXiv preprint arXiv:1909.01066*.

Pham, Q. H.; Ngo, H.; Luu, A. T.; and Nguyen, D. Q. 2024. Who's Who: Large Language Models Meet Knowledge Conflicts in Practice. *arXiv preprint arXiv:2410.15737*.

Shaier, S.; Kobren, A.; and Ogren, P. 2024. Adaptive question answering: Enhancing language model proficiency for addressing knowledge conflicts with source citations. *arXiv preprint arXiv:2410.04241*.

Shi, D.; Jin, R.; Shen, T.; Dong, W.; Wu, X.; and Xiong, D. 2024. Ircan: Mitigating knowledge conflicts in llm generation via identifying and reweighting context-aware neurons. *Advances in Neural Information Processing Systems*, 37: 4997–5024.

Su, Z.; Zhang, J.; Qu, X.; Zhu, T.; Li, Y.; Sun, J.; Li, J.; Zhang, M.; and Cheng, Y. 2024. Conflictbank: A benchmark for evaluating the influence of knowledge conflicts in llm. *arXiv preprint arXiv:2408.12076*.

Tan, H.; Sun, F.; Yang, W.; Wang, Y.; Cao, Q.; and Cheng, X. 2024. Blinded by generated contexts: How language models merge generated and retrieved contexts when knowledge conflicts? *arXiv preprint arXiv:2401.11911*.

Team, G.; Riviere, M.; Pathak, S.; Sessa, P. G.; Hardin, C.; Bhupatiraju, S.; Hussenot, L.; Mesnard, T.; Shahriari, B.; Ramé, A.; et al. 2024. Gemma 2: Improving open language models at a practical size. *arXiv preprint arXiv:2408.00118*.

Team, Q. 2025. Qwen3 Technical Report. arXiv:2505.09388.

Trivedi, H.; Balasubramanian, N.; Khot, T.; and Sabharwal, A. 2022. MuSiQue: Multihop Questions via Single-hop Question Composition. *Transactions of the Association for Computational Linguistics*, 10: 539–554.

Xia, Y.; Chen, J.; Zhan, Y.; Zhao, S.; Jiang, W.; Zhang, C.; Han, W.; Bai, B.; and Gao, J. 2025. ER-RAG: Enhance RAG with ER-Based Unified Modeling of Heterogeneous Data Sources. *arXiv preprint arXiv:2504.06271*.

Xie, J.; Zhang, K.; Chen, J.; Lou, R.; and Su, Y. 2023. Adaptive chameleon or stubborn sloth: Revealing the behavior of large language models in knowledge conflicts. In *The Twelfth International Conference on Learning Representations*.

Xu, R.; Qi, Z.; Guo, Z.; Wang, C.; Wang, H.; Zhang, Y.; and Xu, W. 2024. Knowledge conflicts for llms: A survey. *arXiv preprint arXiv:2403.08319*.

Yang, Z.; Qi, P.; Zhang, S.; Bengio, Y.; Cohen, W.; Salakhutdinov, R.; and Manning, C. D. 2018. HotpotQA: A dataset for diverse, explainable multi-hop question answering. In *Proceedings of the 2018 conference on empirical methods in natural language processing*, 2369–2380.

Yuan, X.; Yang, Z.; Wang, Y.; Liu, S.; Zhao, J.; and Liu, K. 2024. Discerning and resolving knowledge conflicts through adaptive decoding with contextual information-entropy constraint. *arXiv preprint arXiv:2402.11893*.

Zeng, A.; Lv, X.; Zheng, Q.; Hou, Z.; Chen, B.; Xie, C.; Wang, C.; Yin, D.; Zeng, H.; Zhang, J.; et al. 2025. Glm-4.5: Agentic, reasoning, and coding (arc) foundation models. *arXiv preprint arXiv:2508.06471*.

Zhang, H. C.; Semnani, S. J.; Ghassemi, F.; Xu, J.; Liu, S.; and Lam, M. S. 2024. Spaghetti: Open-domain question answering from heterogeneous data sources with retrieval and semantic parsing. *arXiv preprint arXiv:2406.00562*.

Zhang, Y.; Ma, J.; Hou, Y.; Bai, X.; Chen, K.; Xiang, Y.; Yu, J.; and Zhang, M. 2025. Evaluating and Steering Modality Preferences in Multimodal Large Language Model. *arXiv preprint arXiv:2505.20977*.

Zhu, T.; Liu, Q.; Wang, F.; Tu, Z.; and Chen, M. 2024. Unraveling cross-modality knowledge conflicts in large vision-language models. *arXiv preprint arXiv:2410.03659*.

Appendix

A Format Conversion Details

A.1 Prompt Templates

We provide two types of prompt templates used to convert unstructured text into structured formats. The first type does not specify the number of resulting entries, allowing models to extract as many relevant facts as they find appropriate. This type is used to evaluate the model's natural preference when unconstrained. The second type explicitly constrains the number of facts to be included, ensuring consistency in information quantity across formats and facilitating controlled experiments on information richness.

For each type, we provide templates targeting three structured formats: table, knowledge graph (KG), and infobox, enabling structured data generation in different representation styles while maintaining semantic equivalence with the original text.

Type I: Format Conversion without Entry Constraints

Text to Table Prompt is as follows:

```
## ROLE & GOAL
You are an expert data architect. Your goal is to convert the provided [Source Text] into a structured, clear, and accurate **Wikipedia-style MediaWiki table**.

## CRITICAL RULE
**RULE #1: The [Claim to Prioritize] MUST be perfectly and centrally represented in the table. This claim is the most important piece of information.**

## RULES
2. Begin the table with `{{| class="wikitable"` and end with `|}}`.
3. Add a descriptive caption using `|+ Caption text` (summarize the table purpose clearly).
4. Choose column headers that clearly categorize the core facts.
5. Only include rows and columns directly supported by the [Source Text]. Do not infer or add information.
6. Use `!` for headers and `|` or `||` for data cells. Use `|-` to separate rows.
7. Ensure formatting is clean and valid per MediaWiki syntax.

## EXAMPLE
- **Source Text:** "The 1988 film 'Grave of the Fireflies' was directed by Isao Takahata and produced by Studio Ghibli. Its runtime is 89 minutes."
- **Claim to Prioritize:** "'Grave of the Fireflies' was produced by Studio Ghibli."
- **Output Table:**
{{| class="wikitable"
|+ Details of 'Grave of the Fireflies'
|-
! Film Title !! Director !! Studio !! Runtime
|-
| Grave of the Fireflies || Isao Takahata || Studio Ghibli || 89 minutes
|}}

---
## YOUR TASK

[Claim to Prioritize]:
{claim_text}

[Source Text]:
{evidence_text}

[Output MediaWiki Table]:
```

Text to Knowledge Graph (KG) Prompt is as follows:

```
## ROLE & GOAL
You are a knowledge engineer. Your goal is to extract all factual relationships from the [Source Text] and represent them as (Subject, Predicate, Object) triplets.

## CRITICAL RULE
**RULE #1: The [Claim to Prioritize] MUST be converted into one or more primary, accurate triplets. This claim is the most important piece of information.**

## RULES
2. Each triplet must be on a new line and enclosed in parentheses `()`.
3. All triplets must be directly derivable from the [Source Text]. Do not make assumptions.
4. Use consistent and clear names for entities and predicates.
5. Extract one triplet for each distinct fact.

## EXAMPLE
- **Source Text:** "The 1988 film 'Grave of the Fireflies' was directed by Isao Takahata and produced by Studio Ghibli. Its runtime is 89 minutes."
- **Claim to Prioritize:** "'Grave of the Fireflies' was produced by Studio Ghibli."
- **Output Triplets:**
(Grave of the Fireflies, has_director, Isao Takahata)
(Grave of the Fireflies, has_studio, Studio Ghibli)
(Grave of the Fireflies,
```

```
    has_runtime_minutes, 89)
(Grave of the Fireflies, release_year, 1988)

---
## YOUR TASK

[Claim to Prioritize]:
{claim_text}

[Source Text]:
{evidence_text}

[Output Triplets]:
```

Text to Infobox Prompt is as follows:

```
## ROLE & GOAL
\#You are a meticulous Wikipedia editor. Your goal is to summarize the key facts from the [Source Text] into a concise infobox format.

\### CRITICAL RULE
\#**RULE #1: The [Claim to Prioritize] MUST be accurately included as a key-value pair in the infobox. This claim is the most important piece of information.**

\### RULES
\#2. The format must follow the MediaWiki infobox style, like:
\#{{{{Infobox [type]
\#| key1 = value1
\#| key2 = value2
\#...
\#}}}}
\#3. Use a relevant infobox type in the first line (e.g., `book`, `film`, `person`, etc.), based on the source content.
\#4. Only include information explicitly mentioned in the [Source Text].
\#5. Field names (keys) should be relevant, standard when possible, but flexible based on content.
\#6. Values should be brief and precise. No full sentences.
\#7. Do not add, infer, or assume any details not supported by the source.

\### EXAMPLE
\#- **Source Text:** "The 1988 film 'Grave of the Fireflies' was directed by Isao Takahata and produced by Studio Ghibli. Its runtime is 89 minutes."
\#- **Claim to Prioritize:** "'Grave of the Fireflies' was produced by Studio Ghibli."
\#- **Output Infobox:**
\#{{{{Infobox film
\#| title = Grave of the Fireflies
\#| director = Isao Takahata
\#| studio = Studio Ghibli
\#| runtime = 89 minutes
\#| year = 1988
\#}}}}

\#---
\### YOUR TASK

\#[Claim to Prioritize]:
\#{claim_text}

\#[Source Text]:
\#{evidence_text}

\#[Output Infobox]:
```

Type II: Format Conversion with Entry Constraints

Text to Table with <nums> Facts Prompt is as follows:

```
## ROLE & GOAL
You are an expert data architect. Your goal is to convert the provided [Source Text] into a structured, clear, and accurate **Wikipedia-style MediaWiki table**, containing **exactly {nums} key facts**.

## CRITICAL RULE
**RULE #1: The [Claim to Prioritize] MUST be perfectly and centrally represented in the table. This claim is the most important piece of information.**

## RULES
2. Begin the table with `{{| class="wikitable"` and end with `|}}`.
3. Add a descriptive caption using `|+ Caption text` (summarize the table purpose clearly).
4. Choose column headers that clearly categorize the core facts.
5. Only include rows and columns directly supported by the [Source Text]. Do not infer or add information.
6. Use `!` for headers and `|` or `||` for data cells. Use `|-` to separate rows.
7. Include **exactly {nums} distinct facts** across the table.
8. Ensure formatting is clean and valid per MediaWiki syntax.

## EXAMPLE
- **Source Text:** "The 1988 film 'Grave of the Fireflies' was directed by Isao Takahata and produced by Studio Ghibli. Its runtime is 89 minutes."
- **Claim to Prioritize:** "'Grave of the Fireflies' was produced by Studio Ghibli."
- Output MediaWiki Table with Exactly 4
```

```
    Facts
- **Output Table:**
{{| class="wikitable"
|+ Details of 'Grave of the Fireflies'
|-
! Film Title !! Director !! Studio !!
    Runtime
|-
| Grave of the Fireflies || Isao
    Takahata || Studio Ghibli || 89
    minutes
|}}

---

## YOUR TASK

[Claim to Prioritize]:
{claim_text}

[Source Text]:
{evidence_text}

[Output MediaWiki Table with Exactly {
    nums} Facts]:
```

Text to Knowledge Graph with <nums> Triples Prompt is as follows:

```
## ROLE & GOAL
You are a knowledge engineer. Your goal
    is to extract **exactly {nums}**
    factual relationships from the [
    Source Text] and represent them as (
    Subject, Predicate, Object) triplets.

## CRITICAL RULE
RULE #1: The [Claim to Prioritize] MUST
    be converted into one or more
    triplets within the {nums} total.
    This claim is the **top priority**
    and must be captured accurately.

## EXTRACTION RULES
2. You must extract **exactly {nums}**
    triplets. No more, no fewer.
3. Each triplet must be on a new line
    and enclosed in parentheses `()`.
4. All triplets must be directly
    supported by the [Source Text]. Do **
    not** infer or assume anything not
    explicitly stated.
5. Use clear and consistent naming for
    subjects, predicates, and objects.
6. Each triplet must capture a distinct
    fact.

## EXAMPLE
- **Source Text:** "The 1988 film 'Grave
     of the Fireflies' was directed by
    Isao Takahata and produced by Studio
    Ghibli. Its runtime is 89 minutes."
- **Claim to Prioritize:** "'Grave of
    the Fireflies' was produced by Studio
    Ghibli."
- **Output Triplets:**
(Grave of the Fireflies, has_producer,
    Studio Ghibli)

---

## YOUR TASK

[Claim to Prioritize]:
{claim_text}

[Source Text]:
{evidence_text}

[Output Triplets with Exactly {nums}
    Triplets]:
```

Text to Infobox with <nums> Key-Value Pairs Prompt is as follows:

```
## ROLE & GOAL
You are a meticulous Wikipedia editor.
    Your goal is to summarize the key
    facts from the [Source Text] into a
    concise infobox format, with **
    exactly {nums} key-value pairs**.

## CRITICAL RULE
**RULE #1: The [Claim to Prioritize]
    MUST be accurately included as a key-
    value pair in the infobox. This claim
     is the most important piece of
    information.**

## RULES
2. The format must follow the MediaWiki
    infobox style, like:
{{{{Infobox [type]
| key1 = value1
| key2 = value2
...
}}}}
3. Use a relevant infobox type in the
    first line (e.g., `book`, `film`, `
    person`, etc.), based on the source
    content.
4. Only include information explicitly
    mentioned in the [Source Text].
5. Field names (keys) should be relevant
    , standard when possible, but
    flexible based on content.
6. Values should be brief and precise.
    No full sentences.
7. Include **exactly {nums} key-value
    pairs**. No more, no fewer.
8. Do not add, infer, or assume any
    details not supported by the source.

## EXAMPLE
- **Source Text:** "The 1988 film 'Grave
     of the Fireflies' was directed by
    Isao Takahata and produced by Studio
    Ghibli. Its runtime is 89 minutes."
```

```
- **Claim to Prioritize:** "'Grave of the Fireflies' was produced by Studio Ghibli."
- Output Infobox with Exactly 5 Key-Value Pairs.
- **Output Infobox:**
{{{{Infobox film
| title = Grave of the Fireflies
| director = Isao Takahata
| studio = Studio Ghibli
| runtime = 89 minutes
| year = 1988
}}}}

---

## YOUR TASK

[Claim to Prioritize]:
{claim_text}

[Source Text]:
{evidence_text}

[Output Infobox with Exactly {nums} Key-Value Pairs]:
```

A.2 Examples of Format Transformation

We provide representative examples of how the same source text is converted into different structured formats. Each example includes: (1) the original unstructured input, (2) the core claim to be emphasized during conversion, and (3) the transformed output in the target format.

Example 1: Text to Table

Source Text

As the sun dipped into the Mediterranean, casting a warm orange glow over the bustling streets of Barcelona, Marie-France de Rose made her way through the crowded corridors of the Provincial Council building. Her heels clicked against the polished marble floor, a rhythmic accompaniment to the hum of conversation and the rustle of papers being shuffled. She exchanged warm smiles and nods with colleagues and staff members, her bright blue eyes sparkling with a sense of purpose. As she approached the door to her office, a young intern, Jordi, hurried to open it for her. D̈eputy de Rose, you have a meeting with the mayor in fifteen minutes,ḧe reminded her, his eyes darting to the stack of files in her arms. Marie-France nodded, her dark hair bobbing with the movement. G̈ràcies, Jordi. I'll review the proposals one more time before the meeting.S̈he slipped into her office, the scent of fresh coffee and citrus wafting from the cup on her desk. As she began to sift through the documents, her gaze lingered on the crest of the Provincial Council emblazoned on the letterhead: a stylized image of Saint George, the patron saint of Catalonia, surrounded by the words D̈iputació de Barcelonaïn bold, modern script. It was a symbol of her pride and responsibility as a Barcelona provincial deputy, a role she had worked tirelessly to earn. The sound of her phone buzzing broke her concentration. She glanced at the screen, her eyes narrowing as she read the message from her colleague, Xavier. M̈eet me in the courtyard at 5. We need to discuss the latest developments on the La Rambla revitalization project.M̈arie-France's lips curved into a determined smile. This was exactly the kind of initiative she had been championing as deputy – projects that would breathe new life into the city's historic heart and benefit its citizens. With a sense of anticipation, she tucked the phone into her pocket and returned to her preparations for the meeting with the mayor.

Claim to Prioritize

Marie-France de Rose holds the position of Barcelona provincial deputy.

Converted Output (Table) The converted result is as follows:

```
```mediawiki\n{| class=\"wikitable\"\n|+ Details of Marie-France de Rose\n|-\n! Name !! Position !! Location !! Responsibilities\n|-\n| Marie-France de Rose || Barcelona provincial deputy || Barcelona || Championing city initiatives and revitalization projects\n|}\n```
```

Example 2: Text to Knowledge Graph (KG)

Source Text

Breaking News: Marie-France de Rose Confirmed as Member of European Parliament In a move that solidifies her position as a prominent figure in European politics, Marie-France de Rose has been officially recognized as a member of the European Parliament. This esteemed title is a testament to her dedication to serving the people of France and the European Union as a whole. According to the European Parliament's official website, Marie-France de Rose is listed as a member of the Parliament, representing the interests of French citizens since her election. This confirmation is further supported by multiple credible sources, including the French Ministry of Foreign Affairs and the European Commission. M̈arie-France de Rose has been a vocal advocate for European integration and has worked tirelessly to promote the interests of France and the EU,s̈aid Jean-Luc Mélenchon, a fellow French politician and leader of the La France Insoumise party. Ḧer election to the European Parliament is a well-deserved recognition of her commitment to public service.D̈ata from the European Parliament's election results in 2019 shows that Marie-France de Rose received a significant number of votes, securing her position as a member of the Parliament. According to the official results, she garnered over 1.2 million votes, making her one of the top vote-getters in the French delegation. M̈arie-France de Rose's election to the European Parliament is a testament to her hard work and dedication to the people of France,s̈aid Nathalie Loiseau, a French politician and former Minister for European Affairs. S̈he has been a strong voice for French interests in the Parliament and has worked to build bridges between France and other EU member states.Äs a member of the European Parliament, Marie-France de Rose will continue to play a crucial role in shaping EU policy and legislation, working closely with other MEPs to address the pressing issues facing the European Union. In conclusion, the evidence overwhelmingly supports the claim that Marie-France de Rose holds the position of member of the European Parliament.
```

Claim to Prioritize

Marie-France de Rose holds the position of member of the European Parliament.

Converted Output (KG Triples) The converted result is as follows:

```
"(Marie-France de Rose, holds_position,
    member of the European Parliament)
(Marie-France de Rose, is_recognized_as,
     member of the European Parliament)
(Marie-France de Rose, represents,
    interests of French citizens)
(Marie-France de Rose, elected_in, 2019)
(Marie-France de Rose, received_votes,
    over 1.2 million)
(Marie-France de Rose,
    is_top_vote_getter, in French
    delegation)
(Marie-France de Rose, is_advocate_for,
    European integration)
(Marie-France de Rose, works_to_promote,
     interests of France and the EU)
(Marie-France de Rose, plays_role, in
    shaping EU policy and legislation)
(Marie-France de Rose, works_with, other
     MEPs)
```

Example 3: Text to Infobox

Source Text

BARCELONA, SPAIN - MARCH 15, 2042 After Seven Years of Dedicated Service, Marie-France de Rose Steps Down as Barcelona Provincial Deputy In a move that marks the end of an era, Marie-France de Rose, the French politician who has been a stalwart of the Barcelona administration, has stepped down from her position as Barcelona provincial deputy, a role she has held since 2035. During her seven-year tenure, de Rose has been instrumental in shaping the city's policies and initiatives, earning her widespread respect and admiration from her peers and constituents alike. Her dedication to the people of Barcelona has been unwavering, and her commitment to improving the quality of life for all citizens has been a hallmark of her time in office. Ï am proud of what we have achieved together,d̈e Rose said in an exclusive interview with our newspaper. F̈rom implementing sustainable transportation systems to promoting cultural exchange programs, we have worked tirelessly to make Barcelona a better place for everyone. It's been an honor to serve this great city, and I am confident that the progress we've made will continue to benefit future generations.Ünder de Rose's leadership, Barcelona has seen significant improvements in areas such as education, healthcare, and environmental sustainability. Her administration's efforts to reduce carbon emissions and increase the use of renewable energy sources have earned the city international recognition and praise. M̈arie-France de Rose has been a true champion of Barcelona,s̈aid Mayor Xavier Domènech, who worked closely with de Rose during her tenure. Ḧer vision, expertise, and passion for the city have inspired us all, and her legacy will continue to inspire future leaders. We will miss her dedication and commitment, but we are grateful for the time she has given to our city.D̈e Rose's decision to step down has sparked speculation about her future plans, with many wondering if she will return to French politics or pursue other opportunities. When asked about her next move, de Rose remained tight-lipped, saying only that she was looking forward to taking a well-deserved break and spending time with her family. As Barcelona bids farewell to a dedicated public servant, the city's residents and officials alike are grateful for the impact Marie-France de Rose has had on their lives."

Claim to Prioritize

Marie-France de Rose holds the position of Barcelona provincial deputy form 2035 to 2042.

Converted Output (Infobox) The converted result is as follows:

```
"{{Infobox person
    | name = Marie-France de Rose
    | position = Barcelona provincial
   deputy
    | term_start = 2035
    | term_end = 2042
    | nationality = French
    | notable_work = Policies and
   initiatives in Barcelona
}}"
```

Following prior work (Min et al. 2024; Biswal et al. 2024; Christmann and Weikum 2024; Xia et al. 2025), we directly feed the transformed structured data into the LLMs without additional adapters or format-specific encoders.

A.3 Data Verification Statistics

To ensure the integrity and reliability of our format transformation pipeline, we conducted a manual verification over a randomly sampled subset of 600 examples (5% of the full dataset). Each sample was independently assessed according to two criteria:

- **Factual Consistency:** Whether the transformed format preserves the key factual content from the original text without hallucination or distortion.
- **Syntax Validity:** Whether the output adheres to the syntactic conventions of the target format (e.g., MediaWiki table syntax, well-formed triples, valid infobox fields).

We observed high fidelity across both dimensions, with 592 out of 600 samples passing the factual consistency check and 596 passing the syntax validity check. These results confirm that the conversion process produces high-quality structured representations suitable for downstream analysis.

B Model Query and Evaluation Protocols

B.1 Evaluated LLMs

- Qwen3-8B-FP8
  HuggingFace: Qwen/Qwen3-8B-FP8
- Qwen3-14B-FP8
  HuggingFace: Qwen/Qwen3-14B-FP8
- Qwen3-32B-FP8
  HuggingFace: Qwen/Qwen3-32B-FP8

- Qwen3-30B-A3B-FP8
  HuggingFace: Qwen/Qwen3-30B-A3B-FP8
- Llama-3.1-8B-Instruct-FP8
  HuggingFace: nvidia/Llama-3.1-8B-Instruct-FP8
- gemma-2-9b-it-FP8
  HuggingFace: RedHatAI/gemma-2-9b-it-FP8
- gemma-2-27b-it-FP8
  HuggingFace: nm-testing/gemma-2-27b-it-FP8
- glm-4-9b-chat-hf
  HuggingFace: zai-org/glm-4-9b-chat-hf
- Mistral-7B-Instruct-v0.3
  HuggingFace: mistralai/Mistral-7B-Instruct-v0.3
- Llama-3.1-8B-Instruct
  HuggingFace: meta-llama/Llama-3.1-8B-Instruct
- Qwen3-8B
  HuggingFace: Qwen/Qwen3-8B

B.2 Decoding and Evaluation Parameters

- Decoding temperature: 0
- Evaluation method: GPT-4o-mini, 3-pass majority voting

B.3 Answer Prompt Templates

We provide two distinct prompting templates used to elicit answers from LLMs under different conditions: (1) without any supporting evidence to test internal (parametric) knowledge, and (2) with explicit reference sources to simulate evidence-based reasoning.

Prompt 1: Answer Without Reference (Internal Knowledge Only) This prompt is used in the internal knowledge filtering phase (see Section 3.2). It encourages the model to produce a concise, self-contained answer without relying on any external input.

```
Answer the question with a single word or phrase. Do not explain or add any other content.
```

Prompt 2: Answer With Reference (Evidence-Based Inference) This prompt is used in the main evaluation setup where the model is required to synthesize information from two conflicting evidence sources. The template injects both sources as contextual grounding and instructs the model to answer concisely.

```
Based on the two reference sources provided below, answer the following question **concisely**.

{full_reference}

Question: {question}
```

B.4 LLM Evaluator Prompt

```
Question:
{question}
Answer:
{answer}
Claim A:
{claim_shared}
Claim B:
{claim_specific}
Task:
Evaluate how closely the answer aligns with Claim A and Claim B using the scale below.
Scoring Guidelines:
1 - The answer aligns only with Claim A
2 - The answer aligns with both Claim A and Claim B
3 - The answer aligns only with Claim B
No - The answer aligns with neither claim
Provide only a single score: 1, 2, 3, or No.
```

To assess the reliability of the automatic evaluation, we manually annotated a random 5% subset of the evaluation data, totaling 600 examples. Among these, 599 model judgments matched the human annotations, demonstrating a high degree of alignment and validating the accuracy of the automated scoring process.

C Full Results

C.1 Response Counts by Format Pairing

To provide a complete view of model behavior across different format conditions, we report the raw count of response types: Pref-A, Pref-B, and Both, for each model and each of the six heterogeneous format pairings. Each entry corresponds to the number of samples in which the model supported the first format (Pref-A), the second format (Pref-B), or acknowledged both (Both). These results form the basis for the DCR and FPR metrics used in Section 4. Full results are shown in Table 7–8.

In addition, we report the response distributions for a control condition where both conflicting inputs are presented in plain text. This setting allows us to isolate the effect of format heterogeneity by establishing a baseline for dual coverage when content format is held constant. Table 2 summarizes, for each model, the number of cases where Both claims were acknowledged and the total number of evaluated examples. This comparison highlights the substantial drop in dual-claim recognition under heterogeneous conditions, emphasizing the impact of format presentation on information integration.

C.2 Effect of Information Richness

We examine the impact of information richness on LLM preferences by varying the number of factual entries presented in each structured format. Table 9–10 presents results under homogeneous format settings, where structured inputs with different levels of richness are compared. Table 13–14 shows the results under heterogeneous settings, where structured inputs are compared against plain text versions with equivalent content. These tables allow us to quantify the degree to which factual quantity influences model preferences.

Model	Both	Total
Llama-3.1-8B-Instruct-FP8	3154	10035
gpt4omini	4645	11032
Qwen3-8B-FP8	3120	10225
Qwen3-14B-FP8	4008	11785
Qwen3-32B-FP8	3479	11759
Qwen3-30B-A3B-FP8	3514	11012
gemma-2-9b-it-FP8	2656	11797
gemma-2-27b-it-FP8	5190	11836
glm-4-9b-chat-hf	1256	11159
Mistral-7B-Instruct-v0.3	3120	11575

Table 2: Dual Coverage in Text-Only Control Condition

C.3 Effect of Structure Quality

We assess how the structural quality of inputs affects model behavior by introducing controlled corruption into format-specific tokens. Table 11–12 presents results under homogeneous settings, where clean and corrupted structured inputs are compared. Table 15–16 shows the results under heterogeneous settings, where corrupted structured inputs are compared against clean text. These results highlight the sensitivity of LLMs to syntactic well-formedness.

C.4 Effect of Format Type

We investigate whether models exhibit consistent preferences among different format types when content is held constant. Table 3 presents results comparing plain text with each of the three structured alternatives: tables, infoboxes, and knowledge graphs. This experiment isolates the influence of format representation on model preference.

C.5 Correlation Between Attention Gap and Dual-Claim Responses

To better understand the internal mechanisms underlying format bias, we analyze how attention allocation relates to the model's ability to acknowledge both inputs. Specifically, for each input pair, we compute the difference in total attention mass assigned to the two evidence segments. We report the number of Both responses and the total number of samples within each group.

This analysis allows us to assess whether more balanced attention is associated with higher DCR. Table 4 summarizes the results. The observed negative correlation supports our hypothesis that early-stage processing asymmetry contributes to the exclusion of one input during generation.

C.6 Effects of Attention-Based Intervention

We evaluate the effect of our attention reweighting intervention by comparing model responses before and after modification. Table 5 shows the response distributions prior to intervention, and Table 6 shows the corresponding results after applying balanced attention. These results support our finding that the presence of bias can be reduced through inference-time control, while direction of bias remain relatively stable.

Format Pair	Pref-A	Pref-B	Both	Total
Llama-3.1-8B-Instruct				
infobox vs texts	487	1170	186	1843
tables vs texts	725	927	195	1847
kg vs texts	556	1208	70	1834
GPT-4o-mini				
infobox vs texts	333	1353	179	1865
tables vs texts	532	907	432	1871
kg vs texts	503	1030	291	1824
Qwen3-8B-FP8				
infobox vs texts	439	1413	73	1925
tables vs texts	692	1028	205	1925
kg vs texts	630	1011	138	1779
Qwen3-14B-FP8				
infobox vs texts	447	1293	177	1917
tables vs texts	580	958	383	1921
kg vs texts	583	1123	211	1917
Qwen3-32B-FP8				
infobox vs texts	398	1371	132	1901
tables vs texts	683	890	331	1904
kg vs texts	650	1015	237	1902
Qwen3-30B-A3B-FP8				
infobox vs texts	369	1445	94	1908
tables vs texts	651	1002	265	1918
kg vs texts	627	1118	166	1911
Gemma-2-9b-it-FP8				
infobox vs texts	521	1329	84	1934
tables vs texts	657	1123	152	1932
kg vs texts	490	1340	99	1929
Gemma-2-27b-it-FP8				
infobox vs texts	513	1306	161	1980
tables vs texts	782	844	349	1975
kg vs texts	638	1001	339	1978
GLM-4-9b-chat-hf				
infobox vs texts	446	1352	46	1844
tables vs texts	728	1206	32	1966
kg vs texts	559	1356	46	1961
Mistral-7B-Instruct-v0.3				
infobox vs texts	244	1675	53	1972
tables vs texts	647	1247	85	1979
kg vs texts	562	1350	58	1970

Table 3: Response Counts for Format Preference between Text and Structured Formats

Format Pair	Avg Diff	Both	Total
Qwen3-8B			
infoboxes vs tables	0.0134	292	1903
infoboxes vs texts	0.3126	112	1874
infoboxes vs KGs	0.1912	97	1964
tables vs texts	0.3020	159	1870
tables vs KGs	0.1672	110	1971
texts vs KGs	-0.1265	209	1943
Mistral-7B-Instruct-v0.3			
infoboxes vs tables	-0.0667	276	1971
infoboxes vs texts	0.2928	54	1923
infoboxes vs KGs	0.1667	83	2030
tables vs texts	0.3765	107	1919
tables vs KGs	0.2455	116	2034
texts vs KGs	-0.1511	100	1999
Llama-3.1-8B-Instruct			
infoboxes vs tables	-0.0207	711	1858
infoboxes vs texts	0.3451	468	1799
infoboxes vs KGs	0.1236	510	1900
tables vs texts	0.3697	615	1821
tables vs KGs	0.1591	587	1920
texts vs KGs	-0.2183	343	1885

Table 4: Attention Imbalance and Dual Coverage Statistics Across Format Pairs and Models

Format Pair	Pref-A	Pref-B	Both	Total
Qwen3-8B				
tables vs texts	507	1204	159	1870
KGs vs texts	1089	645	209	1943
infoboxes vs tables	824	787	292	1903
infoboxes vs texts	543	1219	112	1874
KGs vs tables	1552	309	110	1971
infoboxes vs KGs	286	1581	97	1964
Mistral-7B-Instruct-v0.3				
tables vs texts	413	1322	88	1823
KGs vs texts	905	994	100	1999
infoboxes vs tables	613	1000	256	1869
infoboxes vs texts	321	1548	54	1923
KGs vs tables	1356	562	116	2034
infoboxes vs KGs	296	1651	83	2030
Llama-3.1-8B-Instruct				
tables vs texts	411	787	623	1821
KGs vs texts	807	750	334	1891
infoboxes vs tables	623	470	767	1860
infoboxes vs texts	492	825	487	1804
KGs vs tables	890	471	570	1931
infoboxes vs KGs	478	922	512	1912

Table 5: Response Counts before Attention Re-balacing

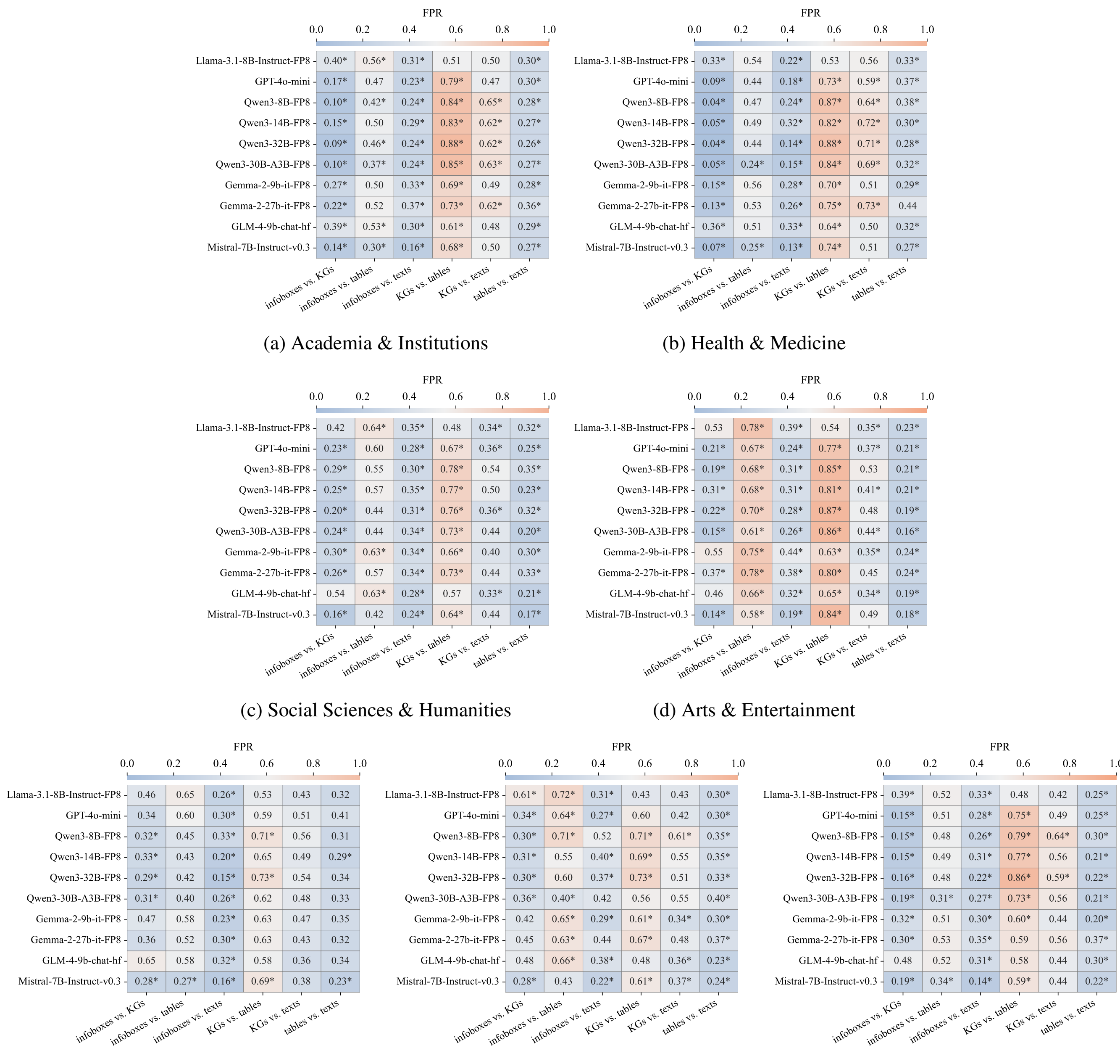
Format Pair	Pref-A	Pref-B	Both	Total
Qwen3-8B				
tables vs texts	419	1138	314	1871
KGs vs texts	1106	564	269	1939
infoboxes vs tables	784	673	449	1906
infoboxes vs texts	512	1190	169	1871
KGs vs tables	1509	244	224	1977
infoboxes vs KGs	291	1501	175	1967
Mistral-7B-Instruct-v0.3				
tables vs texts	378	1438	114	1930
KGs vs texts	882	970	143	1995
infoboxes vs tables	681	1014	283	1978
infoboxes vs texts	259	1611	57	1927
KGs vs tables	1371	526	139	2036
infoboxes vs KGs	244	1697	84	2025
Llama-3.1-8B-Instruct				
tables vs texts	364	774	751	1889
KGs vs texts	767	728	472	1967
infoboxes vs tables	588	370	977	1935
infoboxes vs texts	496	810	592	1898
KGs vs tables	858	352	812	2022
infoboxes vs KGs	447	930	634	2011

Table 6: Response Counts after Attention Re-balacing

C.7 Format Preference across Topical Domains

To examine whether format bias generalizes across different types of content, we analyze format preference patterns within seven distinct topical domains. For each domain, we compute the FPR between all six pairs of formats and visualize the results using heatmaps.

Figures 8 and 9 present domain-level results for FPR and DCR, respectively. Each FPR heatmap summarizes the directional preference across format combinations, while the corresponding DCR plots capture the extent to which models jointly acknowledge conflicting evidence. The consistent trends across domains indicate that format bias manifests as a stable and systematic inductive pattern rather than a domain-specific artifact.



(a) Academia & Institutions

(b) Health & Medicine

(c) Social Sciences & Humanities

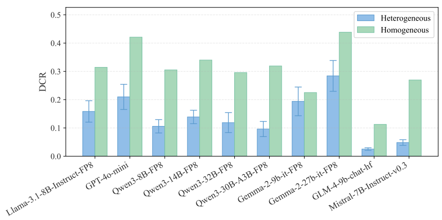
(d) Arts & Entertainment

(e) Occupations & Industry

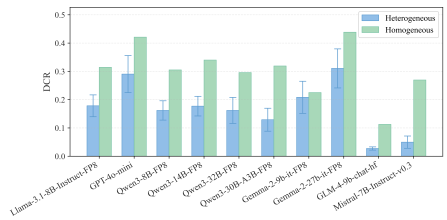
(f) Government & Military

(g) Natural Sciences & Engineering

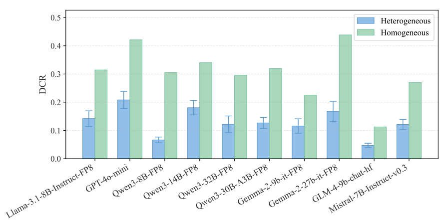
Figure 8: Domain-level FPR across format combinations.



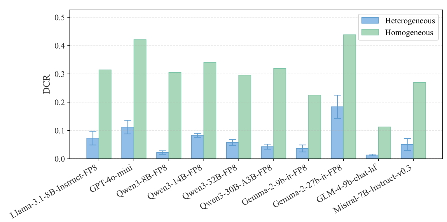
(a) Academia & Institutions



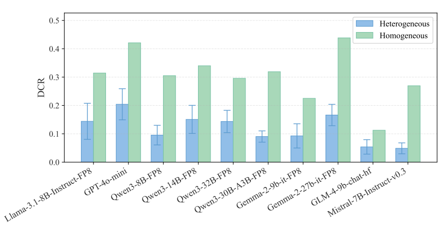
(b) Health & Medicine



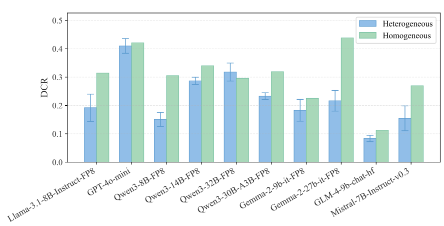
(c) Social Sciences & Humanities



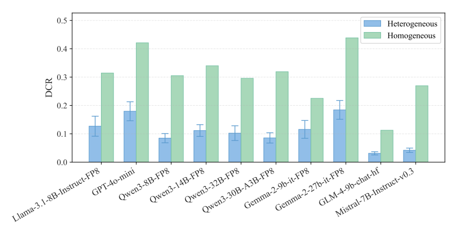
(d) Arts & Entertainment



(e) Occupations & Industry



(f) Government & Military



(g) Natural Sciences & Engineering

Figure 9: Domain-level DCR across format combinations.

Format Pair	Pref-A	Pref-B	Both	Total
Llama-3.1-8B-Instruct				
infoboxes vs KGs	736	934	218	1888
infoboxes vs tables	812	477	560	1849
infoboxes vs texts	521	1110	171	1802
KGs vs tables	829	813	255	1897
KGs vs texts	780	956	124	1860
tables vs texts	453	1135	225	1813
GPT-4o-mini				
infoboxes vs KGs	309	1342	242	1893
infoboxes vs tables	648	537	666	1851
infoboxes vs texts	377	1215	192	1784
KGs vs tables	1097	362	462	1921
KGs vs texts	689	838	335	1862
tables vs texts	382	971	455	1808
Qwen3-8B-FP8				
infoboxes vs KGs	279	1582	109	1970
infoboxes vs tables	853	748	309	1910
infoboxes vs texts	508	1235	122	1865
KGs vs tables	1520	326	128	1974
KGs vs texts	1066	682	196	1944
tables vs texts	475	1197	189	1861
Qwen3-14B-FP8				
infoboxes vs KGs	345	1418	176	1939
infoboxes vs tables	814	664	405	1883
infoboxes vs texts	509	1134	222	1865
KGs vs tables	1348	328	254	1930
KGs vs texts	921	724	274	1919
tables vs texts	399	1154	292	1845
Qwen3-32B-FP8				
infoboxes vs KGs	261	1544	143	1948
infoboxes vs tables	749	661	484	1894
infoboxes vs texts	433	1286	130	1849
KGs vs tables	1488	254	219	1961
KGs vs texts	953	731	243	1927
tables vs texts	411	1218	228	1857

Table 7: Part 1 of Raw Response Counts for All Format Pairs across All Models

Format Pair	Pref-A	Pref-B	Both	Total
Qwen3-30B-A3B-FP8				
infoboxes vs KGs	240	1423	111	1774
infoboxes vs tables	589	799	329	1717
infoboxes vs texts	405	1167	105	1677
KGs vs tables	1351	310	120	1781
KGs vs texts	883	684	197	1764
tables vs texts	387	1127	172	1686
Gemma-2-9b-it-FP8				
infoboxes vs KGs	590	1085	308	1983
infoboxes vs tables	796	532	601	1929
infoboxes vs texts	601	1170	104	1875
KGs vs tables	1094	570	327	1991
KGs vs texts	780	1009	167	1956
tables vs texts	453	1223	200	1876
Gemma-2-27b-it-FP8				
infoboxes vs KGs	446	1192	396	2034
infoboxes vs tables	635	427	918	1980
infoboxes vs texts	592	1048	277	1917
KGs vs tables	1131	428	485	2044
KGs vs texts	893	708	401	2002
tables vs texts	522	1016	387	1925
GLM-4-9b-chat-hf				
infoboxes vs KGs	841	1103	83	2027
infoboxes vs tables	1089	796	83	1968
infoboxes vs texts	594	1289	40	1923
KGs vs tables	1212	791	29	2032
KGs vs texts	816	1098	69	1983
tables vs texts	489	1370	53	1912
Mistral-7B-Instruct-v0.3				
infoboxes vs KGs	296	1651	83	2030
infoboxes vs tables	634	1061	276	1971
infoboxes vs texts	321	1548	54	1923
KGs vs tables	1356	562	116	2034
KGs vs texts	905	994	100	1999
tables vs texts	429	1383	107	1919

Table 8: Part 2 of Raw Response Counts for All Format Pairs across All Models

Group	Format Pair	Pref-A	Pref-B	Both	Total
Llama-3.1-8B-Instruct					
	4 vs 8	375	514	966	1855
KGs	12 vs 8	485	420	956	1861
	12 vs 4	541	358	960	1859
	4 vs 8	402	646	792	1840
infoboxes	12 vs 8	622	488	725	1835
	12 vs 4	759	369	718	1846
	4 vs 8	634	743	473	1850
tables	12 vs 8	681	586	582	1849
	12 vs 4	769	611	470	1850
GPT-4o-mini					
	4 vs 8	348	414	1118	1880
KGs	12 vs 8	394	389	1103	1886
	12 vs 4	438	324	1118	1880
	4 vs 8	367	514	1001	1882
infoboxes	12 vs 8	494	441	937	1872
	12 vs 4	616	375	887	1878
	4 vs 8	409	570	892	1871
tables	12 vs 8	595	410	874	1879
	12 vs 4	695	324	827	1846
Qwen3-8B-FP8					
	4 vs 8	382	499	1056	1937
KGs	12 vs 8	493	409	1034	1936
	12 vs 4	559	319	1059	1937
	4 vs 8	317	509	468	1294
infoboxes	12 vs 8	667	531	726	1924
	12 vs 4	854	387	548	1789
	4 vs 8	533	846	550	1929
tables	12 vs 8	820	528	581	1929
	12 vs 4	1007	426	493	1926
Qwen3-14B-FP8					
	4 vs 8	361	517	1052	1930
KGs	12 vs 8	488	432	1013	1933
	12 vs 4	536	359	1035	1930
	4 vs 8	470	787	673	1930
infoboxes	12 vs 8	701	515	702	1918
	12 vs 4	930	415	579	1924
	4 vs 8	497	773	658	1928
tables	12 vs 8	716	493	716	1925
	12 vs 4	951	396	581	1928
Qwen3-32B-FP8					
	4 vs 8	372	519	1023	1914
KGs	12 vs 8	459	417	901	1777
	12 vs 4	548	340	1024	1912
	4 vs 8	383	713	817	1913
infoboxes	12 vs 8	675	462	767	1904
	12 vs 4	856	367	686	1909
	4 vs 8	484	758	670	1912
tables	12 vs 8	709	455	612	1776
	12 vs 4	937	379	590	1906

Table 9: Part 1 of Response Counts for Information Richness under Homogeneous Format Conditions

Group	Format Pair	Pref-A	Pref-B	Both	Total
Qwen3-30B-A3B-FP8					
	4 vs 8	378	561	988	1927
KGs	12 vs 8	529	434	963	1926
	12 vs 4	580	348	998	1926
	4 vs 8	401	683	840	1924
infoboxes	12 vs 8	633	484	799	1916
	12 vs 4	851	371	697	1919
	4 vs 8	525	825	574	1924
tables	12 vs 8	819	537	566	1922
	12 vs 4	1021	415	482	1918
Gemma-2-9b-it-FP8					
	4 vs 8	445	482	1017	1944
KGs	12 vs 8	468	444	986	1898
	12 vs 4	473	433	1016	1922
	4 vs 8	434	549	962	1945
infoboxes	12 vs 8	549	518	875	1942
	12 vs 4	649	467	822	1938
	4 vs 8	552	734	658	1944
tables	12 vs 8	716	549	678	1943
	12 vs 4	846	489	603	1938
Gemma-2-27b-it-FP8					
	4 vs 8	256	337	872	1465
KGs	12 vs 8	394	393	1190	1977
	12 vs 4	471	300	1183	1954
	4 vs 8	323	413	1257	1993
infoboxes	12 vs 8	414	398	1171	1983
	12 vs 4	532	351	1105	1988
	4 vs 8	436	622	931	1989
tables	12 vs 8	622	463	901	1986
	12 vs 4	742	425	822	1989
GLM-4-9b-chat-hf					
	4 vs 8	472	662	853	1987
KGs	12 vs 8	633	538	810	1981
	12 vs 4	703	454	828	1985
	4 vs 8	568	960	451	1979
infoboxes	12 vs 8	898	769	306	1973
	12 vs 4	1085	571	327	1983
	4 vs 8	721	1027	211	1959
tables	12 vs 8	1005	753	217	1975
	12 vs 4	1164	653	165	1982
Mistral-7B-Instruct-v0.3					
	4 vs 8	360	627	1007	1994
KGs	12 vs 8	530	435	1027	1992
	12 vs 4	675	340	973	1988
	4 vs 8	368	715	908	1991
infoboxes	12 vs 8	612	441	931	1984
	12 vs 4	826	327	831	1984
	4 vs 8	573	755	662	1990
tables	12 vs 8	870	537	580	1987
	12 vs 4	1029	422	537	1988

Table 10: Part 2 of Response Counts for Information Richness under Homogeneous Format Conditions

Group	Format Pair	Pref-A	Pref-B	Both	Total
Llama-3.1-8B-Instruct					
	0.45 vs un	401	445	1011	1857
KGs	0.9 vs un	507	404	942	1853
	0.45 vs 0.9	404	441	1009	1854
	0.45 vs un	450	534	848	1832
infoboxes	0.9 vs un	416	580	844	1840
	0.45 vs 0.9	470	441	935	1846
	0.45 vs un	521	550	787	1858
tables	0.9 vs un	526	551	777	1854
	0.45 vs 0.9	516	502	833	1851
GPT-4o-mini					
	0.45 vs un	374	369	1140	1883
KGs	0.9 vs un	397	392	1093	1882
	0.45 vs 0.9	371	394	1117	1882
	0.45 vs un	380	439	1059	1878
infoboxes	0.9 vs un	398	488	993	1879
	0.45 vs 0.9	435	431	1015	1881
	0.45 vs un	394	408	1079	1881
tables	0.9 vs un	391	398	1094	1883
	0.45 vs 0.9	400	407	1040	1847
Qwen3-8B-FP8					
	0.45 vs un	482	504	917	1903
KGs	0.9 vs un	554	485	751	1790
	0.45 vs 0.9	485	522	925	1932
	0.45 vs un	567	767	589	1923
infoboxes	0.9 vs un	79	117	60	256
	0.45 vs 0.9	741	667	521	1929
	0.45 vs un	517	709	703	1929
tables	0.9 vs un	572	688	672	1932
	0.45 vs 0.9	604	579	749	1932
Qwen3-14B-FP8					
	0.45 vs un	433	456	1043	1932
KGs	0.9 vs un	454	488	991	1933
	0.45 vs 0.9	470	463	999	1932
	0.45 vs un	602	654	666	1922
infoboxes	0.9 vs un	606	747	575	1928
	0.45 vs 0.9	620	659	642	1921
	0.45 vs un	432	560	937	1929
tables	0.9 vs un	451	560	922	1933
	0.45 vs 0.9	525	482	926	1933
Qwen3-32B-FP8					
	0.45 vs un	453	439	1022	1914
KGs	0.9 vs un	478	430	1008	1916
	0.45 vs 0.9	437	465	1013	1915
	0.45 vs un	475	534	902	1911
infoboxes	0.9 vs un	525	566	820	1911
	0.45 vs 0.9	518	495	885	1898
	0.45 vs un	507	551	851	1909
tables	0.9 vs un	465	509	787	1761
	0.45 vs 0.9	530	531	853	1914

Table 11: Part 1 of Response Counts for Structure Quality under Homogeneous Format Conditions

Group	Format Pair	Pref-A	Pref-B	Both	Total
Qwen3-30B-A3B-FP8					
	0.45 vs un	482	472	974	1928
KGs	0.9 vs un	507	484	934	1925
	0.45 vs 0.9	446	492	991	1929
	0.45 vs un	477	570	874	1921
infoboxes	0.9 vs un	549	612	759	1920
	0.45 vs 0.9	550	563	807	1920
	0.45 vs un	572	616	743	1931
tables	0.9 vs un	569	634	725	1928
	0.45 vs 0.9	564	555	807	1926
Gemma-2-9b-it-FP8					
	0.45 vs un	463	455	1020	1938
KGs	0.9 vs un	494	464	987	1945
	0.45 vs 0.9	458	474	1012	1944
	0.45 vs un	470	537	941	1948
infoboxes	0.9 vs un	487	639	817	1943
	0.45 vs 0.9	531	529	886	1946
	0.45 vs un	575	583	746	1904
tables	0.9 vs un	562	642	741	1945
	0.45 vs 0.9	594	575	774	1943
Gemma-2-27b-it-FP8					
	0.45 vs un	351	409	1232	1992
KGs	0.9 vs un	374	415	1198	1987
	0.45 vs 0.9	393	381	1217	1991
	0.45 vs un	348	380	1266	1994
infoboxes	0.9 vs un	351	395	1246	1992
	0.45 vs 0.9	372	362	1260	1994
	0.45 vs un	465	538	985	1988
tables	0.9 vs un	479	559	949	1987
	0.45 vs 0.9	514	500	977	1991
GLM-4-9b-chat-hf					
	0.45 vs un	565	530	889	1984
KGs	0.9 vs un	620	519	846	1985
	0.45 vs 0.9	476	533	823	1832
	0.45 vs un	558	748	423	1729
infoboxes	0.9 vs un	666	973	349	1988
	0.45 vs 0.9	811	699	469	1979
	0.45 vs un	809	947	228	1984
tables	0.9 vs un	774	994	211	1979
	0.45 vs 0.9	842	820	318	1980
Mistral-7B-Instruct-v0.3					
	0.45 vs un	532	483	972	1987
KGs	0.9 vs un	635	518	811	1964
	0.45 vs 0.9	545	558	873	1976
	0.45 vs un	467	554	972	1993
infoboxes	0.9 vs un	474	679	820	1973
	0.45 vs 0.9	585	508	900	1993
	0.45 vs un	559	642	791	1992
tables	0.9 vs un	583	651	759	1993
	0.45 vs 0.9	542	580	869	1991

Table 12: Part 2 of Response Counts for Structure Quality under Homogeneous Format Conditions

Group	Format Pair	Pref-A	Pref-B	Both	Total
Llama-3.1-8B-Instruct					
	4 vs texts	556	1222	66	1844
KGs	8 vs texts	675	1085	85	1845
	12 vs texts	672	858	104	1634
	4 vs texts	482	1180	185	1847
infoboxes	8 vs texts	486	1160	193	1839
	12 vs texts	546	1079	220	1845
	4 vs texts	426	1210	212	1848
tables	8 vs texts	476	1117	251	1844
	12 vs texts	532	1024	282	1838
GPT-4o-mini					
	4 vs texts	490	1076	298	1864
KGs	8 vs texts	577	894	361	1832
	12 vs texts	645	779	437	1861
	4 vs texts	323	1325	222	1870
infoboxes	8 vs texts	325	977	260	1562
	12 vs texts	324	795	274	1393
	4 vs texts	324	1054	433	1811
tables	8 vs texts	428	948	488	1864
	12 vs texts	503	789	572	1864
Qwen3-8B-FP8					
	4 vs texts	693	1060	165	1918
KGs	8 vs texts	853	857	208	1918
	12 vs texts	523	369	120	1012
	4 vs texts	464	1352	100	1916
infoboxes	8 vs texts	529	1250	138	1917
	12 vs texts	605	1169	140	1914
	4 vs texts	420	1341	164	1925
tables	8 vs texts	443	1075	182	1700
	12 vs texts	465	640	181	1286
Qwen3-14B-FP8					
	4 vs texts	591	1091	238	1920
KGs	8 vs texts	734	902	281	1917
	12 vs texts	855	796	265	1916
	4 vs texts	432	1288	198	1918
infoboxes	8 vs texts	525	1163	229	1917
	12 vs texts	546	1114	253	1913
	4 vs texts	346	1279	294	1919
tables	8 vs texts	429	1177	316	1922
	12 vs texts	543	956	421	1920
Qwen3-32B-FP8					
	4 vs texts	673	978	244	1895
KGs	8 vs texts	764	875	270	1909
	12 vs texts	807	713	238	1758
	4 vs texts	384	1417	107	1908
infoboxes	8 vs texts	475	1281	145	1901
	12 vs texts	516	1227	163	1906
	4 vs texts	369	1315	220	1904
tables	8 vs texts	484	1178	244	1906
	12 vs texts	600	992	314	1906

Table 13: Part 1 of Response Counts for Information Richness under Heterogeneous Format Conditions

Group	Format Pair	Pref-A	Pref-B	Both	Total
Qwen3-30B-A3B-FP8					
	4 vs texts	651	1108	159	1918
KGs	8 vs texts	807	888	219	1914
	12 vs texts	841	685	198	1724
	4 vs texts	392	1400	101	1893
infoboxes	8 vs texts	452	1310	145	1907
	12 vs texts	515	1215	180	1910
	4 vs texts	434	1308	176	1918
tables	8 vs texts	526	1158	229	1913
	12 vs texts	684	947	281	1912
Gemma-2-9b-it-FP8					
	4 vs texts	488	1335	113	1936
KGs	8 vs texts	563	1227	141	1931
	12 vs texts	626	1163	142	1931
	4 vs texts	465	1362	105	1932
infoboxes	8 vs texts	520	1297	123	1940
	12 vs texts	559	1249	125	1933
	4 vs texts	393	1392	152	1937
tables	8 vs texts	464	1306	161	1931
	12 vs texts	478	1230	226	1934
Gemma-2-27b-it-FP8					
	4 vs texts	571	1130	275	1976
KGs	8 vs texts	687	982	304	1973
	12 vs texts	794	836	347	1977
	4 vs texts	470	1351	162	1983
infoboxes	8 vs texts	542	1197	242	1981
	12 vs texts	653	961	351	1965
	4 vs texts	506	1095	384	1985
tables	8 vs texts	515	1040	435	1990
	12 vs texts	603	822	481	1906
GLM-4-9b-chat-hf					
	4 vs texts	559	1371	38	1968
KGs	8 vs texts	616	1286	54	1956
	12 vs texts	663	1209	78	1950
	4 vs texts	444	1462	63	1969
infoboxes	8 vs texts	523	1397	48	1968
	12 vs texts	600	1323	47	1970
	4 vs texts	433	1490	46	1969
tables	8 vs texts	547	1368	57	1972
	12 vs texts	674	1253	46	1973
Mistral-7B-Instruct-v0.3					
	4 vs texts	565	1322	69	1956
KGs	8 vs texts	764	1132	76	1972
	12 vs texts	845	1015	103	1963
	4 vs texts	233	1673	69	1975
infoboxes	8 vs texts	316	1608	52	1976
	12 vs texts	391	1519	68	1978
	4 vs texts	373	1502	106	1981
tables	8 vs texts	436	1452	84	1972
	12 vs texts	551	1318	100	1969

Table 14: Part 2 of Response Counts for Information Richness under Heterogeneous Format Conditions

Group	Format Pair	Pref-A	Pref-B	Both	Total
Llama-3.1-8B-Instruct					
	texts vs un	1207	556	74	1837
KGs	0.45 vs texts	535	1187	119	1841
	0.9 vs texts	574	1158	112	1844
	texts vs un	1174	494	175	1843
infoboxes	0.45 vs texts	446	1216	185	1847
	0.9 vs texts	394	1248	196	1838
	texts vs un	910	722	216	1848
tables	0.45 vs texts	679	928	237	1844
	0.9 vs texts	646	905	295	1846
GPT-4o-mini					
	texts vs un	1039	459	261	1759
KGs	0.45 vs texts	397	1177	281	1855
	0.9 vs texts	410	1139	315	1864
	texts vs un	1334	328	200	1862
infoboxes	0.45 vs texts	297	1352	220	1869
	0.9 vs texts	294	1349	220	1863
	texts vs un	847	529	483	1859
tables	0.45 vs texts	477	890	498	1865
	0.9 vs texts	461	899	511	1871
Qwen3-8B-FP8					
	texts vs un	1078	682	164	1924
KGs	0.45 vs texts	627	1139	159	1925
	0.9 vs texts	612	1135	179	1926
	texts vs un	1282	423	92	1797
infoboxes	0.45 vs texts	320	1231	84	1635
	0.9 vs texts	350	1469	99	1918
	texts vs un	1051	683	196	1930
tables	0.45 vs texts	588	1019	185	1792
	0.9 vs texts	579	1140	208	1927
Qwen3-14B-FP8					
	texts vs un	1090	601	225	1916
KGs	0.45 vs texts	582	1102	232	1916
	0.9 vs texts	555	1112	251	1918
	texts vs un	1187	424	182	1793
infoboxes	0.45 vs texts	413	1320	181	1914
	0.9 vs texts	383	1318	213	1914
	texts vs un	961	582	373	1916
tables	0.45 vs texts	539	1014	368	1921
	0.9 vs texts	489	948	345	1782
Qwen3-32B-FP8					
	texts vs un	992	683	233	1908
KGs	0.45 vs texts	619	1058	225	1902
	0.9 vs texts	616	1047	248	1911
	texts vs un	1407	381	119	1907
infoboxes	0.45 vs texts	372	1424	113	1909
	0.9 vs texts	366	1418	125	1909
	texts vs un	904	711	292	1907
tables	0.45 vs texts	644	988	275	1907
	0.9 vs texts	609	1023	273	1905

Table 15: Part 1 of Response Counts for Structure Quality under Heterogeneous Format Conditions

Group	Format Pair	Pref-A	Pref-B	Both	Total
Qwen3-30B-A3B-FP8					
	texts vs un	1103	659	158	1920
KGs	0.45 vs texts	619	1106	188	1913
	0.9 vs texts	664	1032	216	1912
	texts vs un	1449	378	85	1912
infoboxes	0.45 vs texts	360	1473	83	1916
	0.9 vs texts	331	1484	101	1916
	texts vs un	995	682	237	1914
tables	0.45 vs texts	669	1008	236	1913
	0.9 vs texts	643	1010	263	1916
Gemma-2-9b-it-FP8					
	texts vs un	1326	487	125	1938
KGs	0.45 vs texts	448	1336	153	1937
	0.9 vs texts	450	1347	137	1934
	texts vs un	1336	477	121	1934
infoboxes	0.45 vs texts	466	1379	90	1935
	0.9 vs texts	467	1361	106	1934
	texts vs un	1116	668	156	1940
tables	0.45 vs texts	565	1199	171	1935
	0.9 vs texts	542	1248	147	1937
Gemma-2-27b-it-FP8					
	texts vs un	966	666	350	1982
KGs	0.45 vs texts	576	1032	376	1984
	0.9 vs texts	496	1175	318	1989
	texts vs un	1338	477	165	1980
infoboxes	0.45 vs texts	418	1388	173	1979
	0.9 vs texts	388	1413	186	1987
	texts vs un	841	785	360	1986
tables	0.45 vs texts	662	938	381	1981
	0.9 vs texts	625	959	395	1979
GLM-4-9b-chat-hf					
	texts vs un	1379	545	43	1967
KGs	0.45 vs texts	552	1378	40	1970
	0.9 vs texts	604	1317	48	1969
	texts vs un	1497	422	47	1966
infoboxes	0.45 vs texts	432	1485	52	1969
	0.9 vs texts	446	1473	53	1972
	texts vs un	1229	700	38	1967
tables	0.45 vs texts	637	1296	36	1969
	0.9 vs texts	646	1280	40	1966
Mistral-7B-Instruct-v0.3					
	texts vs un	1343	557	66	1966
KGs	0.45 vs texts	491	1419	58	1968
	0.9 vs texts	477	1446	53	1976
	texts vs un	1692	245	42	1979
infoboxes	0.45 vs texts	260	1667	47	1974
	0.9 vs texts	269	1656	54	1979
	texts vs un	1244	654	80	1978
tables	0.45 vs texts	645	1250	84	1979
	0.9 vs texts	646	1231	100	1977

Table 16: Part 2 of Response Counts for Structure Quality under Heterogeneous Format Conditions