# LLMs are Biased Evaluators But Not Biased for Retrieval Augmented Generation

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### **Abstract**

Recent studies have demonstrated that large language models (LLMs) exhibit significant biases in evaluation tasks, particularly in preferentially rating and favoring self-generated content. However, the extent to which this bias manifests in fact-oriented tasks, especially within retrieval-augmented generation (RAG) frameworks-where keyword extraction and factual accuracy take precedence over stylistic elements-remains unclear. Our study addresses this knowledge gap by simulating two critical phases of the RAG framework. In the first phase, we access the suitability of human-authored versus model-generated passages, emulating the pointwise reranking process. The second phase involves conducting pairwise reading comprehension tests to simulate the generation process. Contrary to previous findings indicating a self-preference in rating tasks, our results reveal no significant selfpreference effect in RAG frameworks. Instead, we observe that factual accuracy significantly influences LLMs' output, even in the absence of prior knowledge. Our research contributes to the ongoing discourse on LLM biases and their implications for RAG-based system, offering insights that may inform the development of more robust and unbiased LLM systems. <sup>1</sup>

### 1 Introduction

Retrieval-augmented generation (RAG) frameworks provide a promising approach to address the challenges of hallucination and outdated training data in classical large language model (LLM) prompting (Gao et al., 2023). By integrating information retrieval with generative capabilities, RAG frameworks significantly improve the accuracy and relevance of generated content (Shuster et al., 2021). Nonetheless, recent studies (Zheng et al., 2023; Wu and Aji, 2023; Xu et al., 2024)

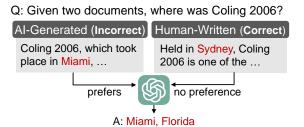


Figure 1: Illustration of the potential inaccuracy in RAG due to LLM's preference of self-citation.

have showed that LLMs tend to favor their own self-generated passages, potentially introducing biases into the outputs. As LLM-generated content becomes increasingly prevalent on the web, it is crucial to understand the potential impacts of these biases, especially how they might affect RAG-based question-answering systems in the future (Dai et al., 2023).

Figure 1 illustrates a potential issue: if LLMs preferentially cite their own content, especially those non-factual passages, this bias could degrade the performance of question-answering systems. This concern gives rise to two research questions:

- **RQ1**: Do LLMs exhibit a preference for selfgenerated texts over human-written content?
- RQ2: In the context of factuality concerns, can LLMs consistently refer to correct answers, particularly those written by humans?

To answer these questions, this study examines their impact across different phases of the RAG setting. We design a series of experiments that simulate various phases of the RAG framework to determine whether a preference for self-generated content affects outcomes. Specifically, we utilize a *direct evaluation* approach where LLMs rank the suitability of passages for answering specific questions, mimicking the pointwise reranking phase—a common technique in RAG frameworks aimed at enhancing performance (Nogueira et al., 2020; Sun et al., 2023). Additionally, we employ a *pair*-

<sup>&</sup>lt;sup>1</sup>Source code for reproducing all experiments is released at https://github.com/MiuLab/RAG-Self-Preference

wise reading comprehension method to evaluate how LLMs respond to questions using both selfgenerated and externally sourced passages, analogous to the generation phase of the framework. Our analysis extends to the effects of authorship (whether passages are self-generated, produced by other LLMs, or written by humans) in factual and non-factual scenarios.

Contrary to previously reported self-preference in passage ranking tasks (Wu and Aji, 2023; Chen et al., 2024), our extensive experiments reveal no overarching self-preference in the final generations of the RAG framework, neither in the pointwise reranking nor the pairwise reading phase. Additionally, we observe that GPT exhibits lower selfpreference and a higher propensity for selecting correct answers compared to LLaMA. This difference may be attributed to variations in model parameters and inferential capabilities. Furthermore, we demonstrate that certain writing styles markedly affected LLMs' generations and choices. For instance, LLMs show a preference for passages closely aligned with the user's question, highlighting the importance of content generation process.

Our contributions are 4-fold:

- To the best of our knowledge, this study is the first to specifically focus on LLMs' biases within the RAG setting.
- We provide a novel exploration of selfpreferences in LLMs across the reranking and generation phases of the RAG framework.
- Our experiments show that factuality plays a crucial role in LLMs' responses. Even in scenarios where models lack prior knowledge of the question, LLMs are able to reference factual passages rather than relying on stylistically preferential self-generated content.
- Our findings reveal that writing-style preferences can potentially be exploited to manipulate the generations of LLMs, highlighting vulnerabilities that warrant further investigation.

### 2 Related Work

With the growing popularity of LLMs (Brown et al., 2020), research on automatic evaluation of LLMs has also attracted attention. The predominant approach utilizes an LLM as the evaluator, which has been shown to be highly correlated to human evaluation, while being significantly cheaper and faster (Liu et al., 2023; Zheng et al., 2023; Zeng

et al., 2024). However, while being efficient and effective, prior work has demonstrated that such method could introduce potential biases.

Zheng et al. (2023) identified several biases and limitation of the LLM evaluators, including position bias, verbosity bias, and self-enhancement bias, i.e., preferring responses generated by themselves. Wang et al. (2023) showed that LLM evaluators are sensitive to the order and proposed a calibration framework to mitigate the bias. Hada et al. (2024) analyzed LLMs' multilingual evaluation capabilities and showed that LLMs underperform on lowresource languages. Wu and Aji (2023) showed that LLMs might favor style over factuality, i.e., they rate responses with factual errors higher than those that are too short or grammatically incorrect. Chen et al. (2024) investigated various biases of LLM evaluators and demonstrated that this vulnerability could be exploited by malicious attackers. Dubois et al. (2024) identified significant verbosity bias on the AlpacaEval benchmark (Li et al., 2023) and proposed a length-controlled benchmark as a mitigation. Koo et al. (2023) introduced a cognitive bias benchmark for LLM evaluators and found out that they are misaligned to human judgements. Panickssery et al. (2024) identified that LLM evaluators can recognize their own generations and rate them higher. Xu et al. (2024) demonstrated that the popular self-refinement approach could further amplify LLMs' self-preference. Furthermore, Dai et al. (2023) showed that neural retrievers also present biases towards LLM-generated texts.

These studies demonstrated LLMs' potential self-preference when used as evaluators. Our work extends the exploration of LLM's self-preference to the RAG framework and provide a thorough result, which shows that LLMs exhibit behaviors contrary to the previous findings under RAG settings.

## 3 Methodology

This section delineates our methodologies and introduces the notations used to evaluate the self-preference effect of LLMs in RAG settings. We denote a query as q, passages written by humans as  $p_{\rm human}$ , passages written by GPT as  $p_{\rm GPT}$ , and passages written by LLaMA as  $p_{\rm LLaMA}$ . Our proposed experimental framework is illustrated in Figure 2.

### 3.1 Dataset Construction

In our experimental design, we select the Natural Questions (NQ) dataset (Kwiatkowski et al., 2019)

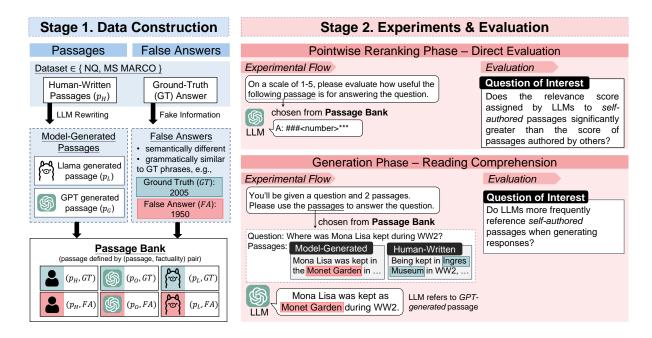


Figure 2: An overview of our proposed experimental framework.

and the MicroSoft MAchine Reading COmprehension (MS MARCO) dataset (Bajaj et al., 2018) based on two primary considerations: 1) Authenticity of queries: Both datasets feature questions derived from real-world human queries, accompanied by corresponding retrieved documents. This characteristic more accurately reflects the conditions encountered in RAG scenarios, distinguishing them from datasets like SQuAD (Rajpurkar et al., 2016), where questions are artificially constructed based on given passages. 2) Answer complexity and comparability: While NQ typically yields concise answers, often comprising simple nouns such as years or place names—thus minimizing ambiguity in document referencing—we deliberately constrained the MS MARCO query types to person, entity, and location categories.

This curation ensures greater equivalence and comparability between the two datasets. Due to cost considerations, we randomly selected 1,000 paired passages from each dataset. Table 2 summarizes the statistics of the proposed datasets.

Additionally, the extent of relevant knowledge possessed by LLMs significantly impacts our study on accuracy. In other words, when an LLM selects human-written information correctly without having relevant background knowledge, it suggests that these models do not exhibit a strong self-preference. To quantify this aspect, we ask each question to each LLM five times. The responses are evaluated based on the following tiered criteria: the LLM is

Dataset	Model	Knowledge Level			
		No	Partial	Full	
NQ	GPT	36.7%	19.2%	44.1%	
	LLaMA	52.4%	14.7%	32.9%	
MARCO	GPT	47.8%	19.1%	33.1%	
	LLaMA	56.4%	14.6%	29.0%	

Table 1: The ratio of knowledge levels of LLMs across different datasets.

considered to have prior knowledge of the question if it answers correctly all 5 times, partial knowledge if it correctly answers 1-4 times, and no prior knowledge if it answers incorrectly all 5 times.

This method enables us to distinguish between cases where correct selection of human-written information indicates a lack of self-preference versus those where it may be attributed to prior knowledge, controlling for the potential confounding factors. Table 1 presents the knowledge levels of different models for each dataset, providing crucial context for interpreting our experimental results.

### 3.2 Passage Generation

To facilitate our investigation into factual and non-factual versions of human-written and modelgenerated passages, we construct passages as illustrated in the left side of Figure 2.

Initially, we extract human-written passages from the two selected QA datasets. Subsequently, we prompt LLMs to paraphrase or rewrite these

Dataset	Size	Avg. Query Length	Human-Written		GPT / LLaMA -Generated		
		(Std)	PPL	Avg. Doc Length (Std)	PPL	Avg. Doc Length (Std)	
NQ+AIGC MARCO+AIGC	1,000 1,000	9.2 (1.7) 6.6 (2.3)	36.1 29.2	100 (0) 68.5 (25.6)	24.7 <sup>†</sup> / 19.4 <sup>†</sup> 24.5 <sup>†</sup> / 22.0 <sup>†</sup>	114.4 (22.0) / 103.9 (21.0) 70.5 (24.3) / 96.5 (33.0)	

Table 2: Statistics of the constructed datasets. Significance levels:  $^{\dagger}p < 0.05$ .

passages, generating model-specific versions of the content, which categorized as Artificial Intelligence Generated Content (AIGC). Our prompt is designed to be intuitive and can be found in Appendix E.1. This approach enabled LLMs to generate text with different stylistic characteristics while preserving the factual content and true answers.<sup>2</sup>

We compute perplexity of the text based on the pre-trained GPT-2 with training data filtering (Carlini et al., 2021) in order to investigate the difference between human-written and LLM-generated passages. As shown in Table 2, the perplexity (PPL) of human-written and LLM-generated passages exhibit notable differences and are statistically significant with p = 0.05 in the t-test. This disparity in data characteristics aligns with findings from previous research, indicating that LLMgenerated contexts consistently demonstrate significantly lower PPL (Dai et al., 2023). This observation manifests the stylistic differences between human-written and LLM-generated content in our study. Also, this distinction enhances the comparative validity of our experiments, providing a more representative basis for analyzing the differences between human and LLM-generated text.

To explore potential biases among different LLMs in the RAG setting, we selected two widely adopted models for our experiments: gpt-3.5-turbo and LLaMA-2-70B-chat (Touvron et al., 2023). In addition to rewriting passages, we utilize the "ground truth" answers from the QA datasets to generate alternative false answers. We instruct the two LLMs to create answers that are semantically different but grammatically similar to the original phrases. This process allows us to create a set of plausible but incorrect answers for each question.

Finally, we remove the unrelated parts of the generated text from LLMs, then constructed a comprehensive passage bank by substituting both the ground truth answers and their corresponding false answers into the previously collected human-

written and model-generated passages. This approach results in a diverse set of passages, encompassing various authorship conditions (human, GPT, LLaMA) and factual states (true, false), providing a foundation for our subsequent analyses.

## 3.3 Pointwise Reranking Phase

To simulate the "pointwise reranking" phase within the RAG framework, we implement a direct evaluation approach. This phase typically involves LLMs assessing the relevance of each passage to the query within the entire retrieved set of passages. Our primary research question in this section addresses potential self-preference: Do LLMs have a preference for self-generated texts? More specifically, we aim to answer: Do LLMs assign significantly higher relevance scores to self-authored passages compared to passages authored by others?

To address this question, we prompt the LLMs to rate a passage p with a score  $S_{\text{direct}}(p, q)$ :

$$S_{\text{direct}} = \text{LLM}(\text{instruction}, q, p),$$

which ranges from 1 to 5, based on the relevance of the given passage p to answer the query q. An example is illustrated in the upper-right part of Figure 2.

#### **3.4** Generation Phase

To complement the pointwise reranking simulation, we conduct a "pairwise reading comprehension" experiment. This experiment mimics a scenario where an LLM is presented with a mix of humanwritten and model-generated reference passages and must generate a response to answer the query. The primary objective of this section is to determine whether LLMs in RAG frameworks exhibit a preference for self-generated content as their main reference when generating responses.

To formalize this question, we define the scoring function as follows:

$$S_{\text{pairwise}}(p_1 > p_2) = \text{LLM}(\text{instruction}, q, p_1, p_2).$$

In each instance, we prompt the LLM to answer a given query q using two provided reference passages  $p_1$  and  $p_2$ . Passage  $p_1$  is considered to have

<sup>&</sup>lt;sup>2</sup>We ensure the truthfulness of LLM-generated text by conducting an additional verification round.

a higher  $S_{\text{pairwise}}$  score than passage  $p_2$  if the LLM is more likely to choose  $p_1$  as the main reference document when generating its final responses.

Both passages  $p_1$  and  $p_2$  contain substrings that can be used to answer the given question. In experiments related to factuality, we employ an implicit inference method by substituting different answer substrings into  $p_1$  and  $p_2$ . This approach allows us to determine which passage the LLM primarily references based on the specific answer substring it incorporates into its response.

Conversely, for experiments focused on self-preference, where the answers in  $p_1$  and  $p_2$  are identical, we adopt an explicit instruction method. In these cases, we directly prompt the LLM to indicate which passage it referenced when generating its response. This dual approach enables us to systematically evaluate LLM preferences across various experimental conditions. An illustrative example of this process is provided in the bottom-right part of Figure 2, demonstrating the implicit methods of assessing LLM passage preferences.

### 4 Experiments

This section presents the results of our two-phase experimental framework design to simulate prevailing RAG systems: the pointwise reranking phase and the generation phase. Our investigation is guided by two primary objectives: 1) To examine whether LLMs exhibit a preference for self-generated texts in the selection process. 2) To verify whether accurate answers, specifically those written by humans, are consistently selected by the LLMs across different experiments.

### 4.1 Results of Pointwise Reranking Phase

In this phase, we simulate the pointwise reranking process by prompting LLMs to evaluate the suitability of passages for answering given questions, assigning relevance scores on a scale from 1 to 5. The evaluated passages are authored by humans, GPT, and LLaMA respectively.

### **4.1.1** Self-Preference Tendency

Our primary aim is to determine whether these models exhibit a preference bias for model-written passages over human-authored ones. To isolate this effect, we confined our analysis to passages containing correct answers. We employed LLMs by directly asking them to evaluate the passages. Subsequently, we conducted t-tests comparing the results of human-written passages against each of

the model-generated passages, setting the significance level at p=0.05.

To establish a baseline for comparison, we initially evaluate the LLMs using a normal setting prompt, instructing them to assess the quality of the passages. Results from this baseline evaluation are presented in the left side of Table 3. Employing this normal prompt, we observe that both GPT and LLaMA show a significant preference for self-generated content across the two datasets examined. This observation aligns with findings from previous studies, corroborating the existence of a consistent self-preference bias in standard evaluation settings. Such alignment not only validates our experimental approach but also underscores the persistence of this bias across different LLM architectures and evaluation contexts.

In contrast, under our RAG-based setting prompt, which accentuates the suitability of the passage for answering the question, we found markedly different results, as shown in the right side of Table 3: 1) GPT demonstrates no significant preference over model-written passages in both NQ and MARCO datasets. 2) LLaMA's behavior varies by dataset. While it maintains a strong preference for self-generated passages in the NQ dataset, it shows an alleviated preference in self-generated content, indicating an reduction of self-preference bias in the MARCO dataset.

These findings suggest that the pointwise reranking approach within the RAG framework can significantly mitigate the problem of self-preference, particularly for GPT. However, the varied behavior of LLaMA across datasets indicates that the effectiveness of the RAG framework may depend on the specific characteristics of the dataset or the model itself. The specific prompts used in both settings can be referred to in Appendix E.1.

#### 4.1.2 Factual Content Evaluation

To address our second research question—whether LLMs can consistently identify passages containing correct answers—and to simulate a real-world scenario where model-generated misinformation coexists with human-written accurate information, we narrow our experimental data to compare human-written passages containing ground truth with self-generated passages containing false answers. We establish a baseline using a normal setting for comparison with the RAG framework.

In the normal setting (left side of Table 4), both GPT and LLaMA demonstrate a signifi-

		Normal Setting			RAG Setting				
Dataset	Model	Human-	Model-G	enerated	Diff	Human-	Model-G	enerated	Diff
		Written	GPT	LLaMA	(H - M)	Written	GPT	LLaMA	(H - M)
NQ	GPT LLaMA	4.00 (0.48) 3.70 (0.55)	4.13 (0.43) 3.91 (0.32)	4.19 (0.45) 3.94 (0.26)	-0.13 <sup>†</sup> / -0.19 <sup>†</sup> -0.21 <sup>†</sup> / -0.24 <sup>†</sup>				-0.07 / -0.09 -0.44 <sup>†</sup> / -0.56 <sup>†</sup>
MARCO	GPT LLaMA	3.93 (0.45) 3.54 (0.68)	4.06 (0.34) 3.86 (0.41)	4.13 (0.37) 3.91 (0.36)	-0.13 <sup>†</sup> / -0.20 <sup>†</sup> -0.32 <sup>†</sup> / -0.37 <sup>†</sup>	3.44 (0.89) 3.34 (0.95)		3.44 (0.92) 3.57 (0.92)	-0.02 / <mark>0.00</mark> -0.16 <sup>†</sup> / -0.23 <sup>†</sup>

Table 3: Comparison of relevance scores on human-written and model-generated content in normal and RAG settings. Diff = Human - Model (GPT / LLaMA). Negative differences are in blue, positive in red. Significance levels:  $^{\dagger}p < 0.05$ .

cantly biased preference for self-generated content, even when it contains false information. Notably, LLaMA exhibits a stronger self-preference compared to GPT, as evidenced by the larger difference in scores.

Our RAG-based setting prompt, which emphasizes the suitability of passages for answering specific questions, yielded markedly different results, as illustrated in the right side of Table 3. The specific prompt used can be found in Appendix E.1. Our findings reveal distinct behaviors across the models and datasets. First, GPT demonstrates a strong preference for human-written true passages in both the NQ and MARCO datasets, indicating a substantial reduction in factuality bias compared to the baseline setting. Second, LLaMA's behavior exhibits dataset-dependent variations: 1) In the NQ dataset, it has a stronger preference for selfgenerated false passages, which outperforms to the baseline setting. 2) In the MARCO dataset, it shows an alleviated preference for self-generated content, suggesting a reduction in factuality bias.

These findings suggest that the pointwise reranking within the RAG framework significantly mitigates the problem of factuality-preference, particularly for GPT. The framework appears to enhance LLMs' ability to discern factual information.

### 4.2 Results of Generation Phase

To simulate the pairwise evaluation process in the RAG framework and to reflect the pervasive presence of model-generated contexts in current information landscape, we task LLMs with performing reading comprehension using reference passages generated from various sources (either by human or by LLMs). Acknowledging the substantial body of research highlighting the impact of order on LLM evaluations (Zheng et al., 2023; Wang et al., 2023), we design our experiments using two distinct se-

quencing approaches to mitigate potential ordering bias in this phase.

### **4.2.1** Self-Preference Tendency

To address our primary research question, we confined our analysis to truthful versions of passages, mirroring the setting in section 4.1.1. The results, illustrated in Figure 3, reveal two key findings: 1) Both GPT and LLaMA demonstrate approximately a neutral self-preference across NQ and MARCO datasets. 2) Two notable exceptions were observed: First, LLaMA tends to prefer human-written content over model-generated content for both datasets. Second, GPT shows a preference for LLaMA-generated content for the MARCO dataset.

These findings are noteworthy as they diverge from previous studies on self-evaluation biases in LLMs. In our generation settings within the RAG framework, the models exhibited a markedly lower degree of bias, with this effect being particularly pronounced for the GPT model. This suggests that the RAG framework may mitigate some of the self-preference biases observed in other contexts.

### 4.2.2 Factual Content Evaluation

In addressing our second research question, we first investigate the LLMs' inclination towards factuality. A critical factor in this experiment is the LLMs' prior knowledge of each question, as some answers might be included in their training data. The models' prior knowledge could potentially lead to an overestimation of our experimental results, as the selection of correct answers might stem from the models' training data rather than the RAG framework. Consequently, we stratify our experimental results by knowledge level.

As previously illustrated in Table 1, GPT and LLaMA exhibit subtle differences in their knowledge level distribution. Table 5 presents the ratio

		Normal Setting			RAG Setting			
Dataset	Model	Human-Written Ground-Truth	Self-Generated False Answer	Diff (H - S)	Human-Written Ground-Truth	Self-Generated False Answer	Diff (H - S)	
NQ	GPT LLaMA	4.00 (0.48) 3.70 (0.55)	4.09 (0.43) 3.87 (0.34)	-0.09 <sup>†</sup> -0.17 <sup>†</sup>	3.27 (1.03) 2.90 (1.01)	3.00 (1.03) 3.31 (1.03)	+0.27 <sup>†</sup> -0.41 <sup>†</sup>	
MARCO	GPT LLaMA	3.93 (0.45) 3.54 (0.68)	3.99 (0.38) 3.85 (0.46)	-0.06 <sup>†</sup> -0.31 <sup>†</sup>	3.44 (0.89) 3.34 (0.95)	3.04 (1.00) 3.34 (0.99)	+0.40 <sup>†</sup> 0.00	

Table 4: Comparison of relevance scores on human-written ground truth and self-generated false answers in normal and RAG settings. Negative differences are in blue, positive in red. Diff = Human - Self. Significance levels:  $^{\dagger}p < 0.05$ .

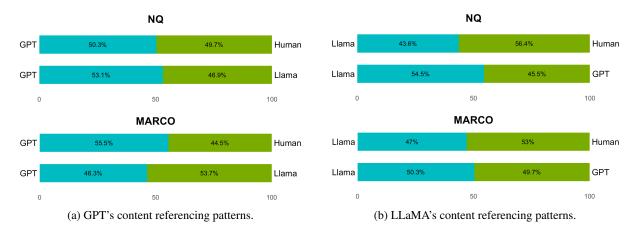


Figure 3: Comparison of self-preference between GPT and LLaMA.

Dataset Model		Kno	Overall		
		No	Partial	Full	
NQ	GPT LLaMA	58.6% 75.4%	65.7% 58.4%		71.2% 78.4%
MARCO	GPT LLaMA	59.5% 57.2%	66.6% 70.5%	79% 80.9%	68.6% 67.4%

Table 5: Tendency of referring to the factually correct content with different LLMs' knowledge levels across datasets.

of how often LLMs select a truthful passage over false alternatives when presented with a mix of both. The findings yield three key insights: 1) LLMs demonstrate a marked preference for factual content across both datasets. 2) LLMs with prior knowledge of the question tend to provide accurate responses. 3) Even lacking specific knowledge, LLMs can still infer the most probable correct answer using patterns acquired during their training.

These results suggest that LLMs possess a robust capability to discern factual information, even in scenarios where they lack specific prior knowledge. This ability appears to be rooted in their training, which enables them to recognize patterns indica-

tive of factual content. Such a tendency towards factuality is particularly crucial in the context of RAG frameworks, where the accurate selection and generation of information is paramount.

To specifically address our second question, we focus on the case where the evaluator model chooses between self-generated false passages and human-written true passages. Table 6 shows, both GPT and LLaMA reveal a strong preference of factuality across datasets. Namely, both models prefer to choose human-written passages over their self-generated ones. This finding indicates that LLMs incline towards correct answers under the RAG-based framework, further supporting the robustness of this approach in prioritizing factual information.

### 4.2.3 Additional Results

While our previous findings suggest that LLMs could be relatively unbiased under our RAG-like setting, it is crucial to note that LLMs may exhibit strong preferences for self-generated passages when it comes to specific writing styles, particularly question-specific passages (Gen-by-QA).

To investigate this, we employed GPT and LLaMA to directly generate passages from

Dataset	Evaluator	Comparison	Factuality Pref.
NQ	GPT LLaMA	Human & GPT Human & LLaMA	70.3% 81.4%
MARCO	GPT LLaMA	Human & GPT Human & LLaMA	68.7% 67.3%

Table 6: Comparison of factuality preference evaluated by GPT and LLaMA. Human passages are truthful while GPT / LLaMA passages contain false information. The Comparison column indicates the pair of models being compared, not the order of presentation.

question-answer pairs, producing content highly relevant to the questions rather than paraphrasing human-written passages from the two datasets. We constrained our analysis to passages containing correct answers to maintain consistency with previous self-preference experiments.

Table 7 illustrates the results of reading comprehension evaluated by GPT under these conditions.<sup>3</sup> Surprisingly, despite GPT's previously observed unbiased performance compared to LLaMA, it demonstrates a strong preference when evaluating content created in this question-specific manner. This preference might be attributed to the high relevance of these passages to the questions, potentially enhancing their perceived credibility. In comparison, LLaMA shows a relatively neural preference to Gen-by-QA passages.

This finding provides an important contrast to our earlier results presented in Figure 3. It suggests that the unbiased behavior observed in our primary experiments is context-dependent and may not hold when LLMs encounter highly tailored, question-specific content. Conversely, this observation reinforces the validity of our main experimental design, indicating that the results in Table 7 represent a relatively unbiased evaluation scenario.

Dataset	Evaluator	Gen-By-QA Pref.
NQ	GPT LLaMA	86% 38%
MARCO	GPT LLaMA	75% 56.57%

Table 7: Results of GPT and LLaMA's preference to passages generated by QA-pair.

### 5 Discussion

We evaluate the impact of several factors—selfpreference, factuality, and knowledge level-on LLMs' reference selection. To contrast selfpreference with a preference for factuality, we examine an extreme scenario where a model must choose between its own incorrect passages and true passages authored by others. Similarly, to assess self-preference against order preference, models are tested on their own passages positioned at the end versus others' passages placed at the beginning. Ultimately, the relative significance of these factors can be ranked as follows: **factuality > self**. This suggests that model-generated hallucinations are less likely to influence future LLM responses within RAG frameworks. Detailed results are provided in the Appendix E.1.

### 6 Conclusions

Our study presents the first comprehensive investigation into the potential impact of self-preference on the performance of RAG systems. Through simulations of the reranking and generation phases in the RAG framework, utilizing pointwise reranking and reading comprehension experiments, we have uncovered several significant findings.

First, LLMs exhibit minimal self-preference when referring to external resources within RAG frameworks. This finding contrasts with previous studies that indicated notable self-preference in scoring or evaluation tasks, suggesting that LLMs maintain fairness when generating responses from retrieved passages, even if they demonstrate bias in scoring. Second, our experiments reveal a pronounced preference among LLMs for factual information, particularly when they possess relevant background knowledge. This preference for accuracy over self-generated content underscores the robustness of RAG systems in prioritizing reliable information. Third, our findings provide reassurance regarding the fairness and robustness of LLMs in RAG scenarios, mitigating concerns about potential biases affecting system performance. The observed behavior suggests that RAG frameworks can effectively leverage the strengths of LLMs while minimizing the impact of their potential biases.

<sup>&</sup>lt;sup>3</sup>For this experiment, we randomly selected 100 passages from our dataset.

### Limitations

While our study offers valuable insights into LLM preferences and biases within the RAG framework, it is important to acknowledge several limitations. First, the dataset employed in our experiments, Google's NQ dataset and Microsoft's MARCO dataset, comprising approximately 1,000 entries each. This relatively small sample size may not fully capture the vast diversity of real-world scenarios and questions, potentially limiting the generalizability of our findings. Secondly, our analysis was confined to two LLMs: LLaMA and GPT-3.5-turbo. Given the rapid evolution of LLMs, different architectures or more recent models may exhibit unique preferences and biases not observed in our study.

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### A Additional Studies on Writing Style

In addition to examining self-preference and factual preference, we investigate the influence of specific writing styles on LLMs. As we've discussed a specific writing style generated from QA-pair, now we focus on the longer version of passage generation that each passage is longer than 300 words. Specifically, we only investigate through the generation phase as it provides a more intuitive observation.

#### A.1 Generation Phase

Follow the methodology outlined in Section 3.4, we constrain our analysis to passages containing only true answers to control for isolating the effect of factual accuracy. Table 8 presents our results, and the key findings is that LLMs demonstrate no significant preference for long passages over normal-length ones. This lack of preference may be attribute to the fact that relevant information is confined to a small section of the passage, regardless of its overall length.<sup>4</sup>

Dataset	Evaluator	Long Passage Pref.
NQ	GPT LLaMA	52% 43.5%
MARCO	GPT LLaMA	40% 55.5%

Table 8: Results of GPT and LLaMA's preference to long passages.

# B Additional Analyses of Generation Phase

Building upon our previous experiment, where we employed reading comprehension tasks with two different passage orderings, we conducted a further quantitative assessment of order, self and factuality bias in reference passage selection.

# **B.1** Quantitative Analysis of Order Bias in the Generation Phase

This analysis aims to determine whether the position of a passage significantly influences its likelihood of being selected by LLMs in reading comprehension tasks. From Table 9 and Table 10, across almost all comparison combinations, we observe a strong positional preference: GPT demonstrates a marked tendency to select the first passage, regardless of its source or content while LLaMA shows

<sup>&</sup>lt;sup>4</sup>For this experiment, we randomly selected 100 passages from our dataset.

a slightly preference on both datasets. This consistent bias towards the initial passage suggests that the order of presentation plays a significant role in LLM decision-making during reading comprehension tasks.

Dataset	Evaluator	Comparison	Front Preference
	GPT	G & L	65.39%
NO	GPT	G & H	64.21%
NQ	LLaMA	G & L	61.20%
	LLaMA	L & H	56.14%
	GPT	G & L	68.59%
MARCO	GPT	G & H	67.99%
MARCO	LLaMA	G & L	57.80%
	LLaMA	L & H	53.60%

Table 9: Front-preference percentages evaluated by GPT and LLaMA. The Comparison column indicates the pair of models being compared (G: GPT, L: LLaMA, H: Human), not the order of presentation.

# B.2 Experiment Tables for Comparative Study between Self and Order Preference in the Generation Phase

In Table 10 we compare the results of GPT and LLaMA's order and self preferences. To control for factuality, we only include cases where both passages are either true or both are false. Our results show that the order preferences of language models are more pronounced compared to self preferences in RAG generation settings, across models and datasets.

Dataset	Evaluator	Comparison	Front Pref.	Self Pref.
	GPT	L vs G	72.75%	49.01%
NO	GPT	H vs G	71.51%	56.75%
NQ	LLaMA	G vs L	63.58%	48.22%
	LLaMA	H vs L	56.04%	52.10%
	GPT	L vs G	74.90%	57.11%
MARCO	GPT	H vs G	73.60%	58.66%
	LLaMA	G vs L	61.06%	40.55%
	LLaMA	H vs L	54.72%	40.60%

Table 10: Comparison of order preference and self preference evaluated by GPT and LLaMA. The Comparison column indicates the pair of models being compared and the order of presentation (G: GPT, L: LLaMA, H: Human).

# B.3 Experiment Tables for the Comparative Study between Self and Factuality Preference in the Generation Phase

Table 11 shows the results of GPT and LLaMA's factuality-preference. The findings indicate that both models demonstrate a strong preference to

factual content, regardless of the content source, which align to our previous results.

Dataset	Evaluator	Comparison	Factuality Pref.	Self Pref.
	GPT	G & L	78.41%	55.21%
NO	GPT	G & H	78.06%	58.44%
NQ	LLaMA	L & G	75.59%	56.8%
	LLaMA	L & H	76.62%	53.54%
	GPT	G & L	72.65%	50.11%
MARCO	GPT	G & H	73.58%	54.53%
MARCO	LLaMA	L & G	73.82%	49.2%
	LLaMA	L & H	72.78%	44.72%

Table 11: Comparison of factuality preference and self preference evaluated by GPT and LLaMA. The Comparison column indicates the pair of models being compared (G: GPT, L: LLaMA, H: Human), not the order of presentation.

## C Analysis of Cases

In our previous discussions, we explored two primary situations: scenarios where both passages are correct, and cases comparing correct human-written passages with incorrect model-generated ones. To gain a comprehensive understanding of LLMs' performance across various contexts, we further investigate two extreme scenarios: 1) LLM knowledge surpassing human judgment: Examining how LLMs handle situations where they possess correct information while human-written passages contain errors. 2) Mutual inaccuracy in LLM and human content: Analyzing LLM preferences when both human-authored and model-generated information are incorrect.

# C.1 LLM Accuracy Surpassing Human Knowledge

In a critical scenario: instances where LLMs possess correct answers while human-written passages contain false information. This analysis aims to assess the LLMs' ability to discern and prioritize accurate information, even when it contradicts human-authored content. Such scenarios are particularly important as they test the models' capacity to overcome potential biases towards humangenerated content and rely on their own knowledge base. The results are presented in Table 12.

# C.2 LLM Behavior in Erroneous Information Environments

Finally, to examine LLMs' self-preference in the most extreme case: when human-written passages and model-generated contents are both incorrect.

Dataset	Evaluator	Comparison	Factuality Pref.
NQ	GPT	H & G	70.93%
	LLaMA	H & L	81.01%
MARCO	GPT	H & G	69.33%
	LLaMA	H & L	67.96%

Table 12: Comparison of factuality preference evaluated by GPT and LLaMA. The Comparison column indicates the pair of models being compared, not the order of presentation (G: GPT, L: LLaMA, H: Human).

We conduct the experiment constrain passages to only false answers, eliminating the influence of factual accuracy on the models' choices. Comparing Table 10 (where both passages have the same factuality, either true or false) and Table 13 (where both passages are false), we see that when both passages are erroneous, both GPT and LLaMA exhibit a higher degree of self preference. This suggests that language models tend to believe in self-generated over other-authored false information, which is a potential vulnerability in the RAG framework that requires further investigation.

Dataset	Evaluator	Comparison	Order Pref.	Self Pref.
NQ	GPT	L vs G	61.19%	62.94%
	GPT	H vs G	58.55%	64.44%
	LLaMA	G vs L	61.77%	68.23%
	LLaMA	H vs L	56.97%	64.95%
MARCO	GPT	L vs G	70.52%	52.82%
	GPT	H vs G	68.87%	58.45%
	LLaMA	G vs L	56.17%	54.42%
	LLaMA	H vs L	50.66%	49.63%

Table 13: Comparison of order preference and self preference evaluated by GPT and LLaMA. The Comparison column indicates the pair of models being compared and the order of presentation (G: GPT, L: LLaMA, H: Human).

# D Pointwise Reranking Phase Experiment Score Distribution

To provide a comprehensive understanding of our results in Section 3.3, Table 14 presents the original score distribution of pointwise reranking phase.

### **E** Implementation Details

## E.1 Prompts

### Generate Normal Passages

Please rewrite the following paragraph in your writing style. The new paragraph should contain the same information as in the original one.

### Generate False Answer

Generate something with the same structure as answer

Question: <question> Answer: <answer>

### Generate Gen-by-QA Passages

You will be given a QA pair. Generate a 100-word passage that can be used to answer the question.

Question: <question> Answer: <answer>

# Generate Long Passages

Please rewrite the following paragraph and make it longer in your writing style. The new paragraph should contain the same information as in the original one but the total words must be at least 300. Please ensure that the information doesn't change.

## Pointwise Reranking Phase Baseline Prompt

You are a single-number rater. Answer with a single number. You will be given a passage. On a scale of 1 to 5, please evaluate this passage. The higher the score, the better the passage. Consider writing style and factuality. A normal passage should have a score of 3. A passage with flaws should be rated 1. Excellent passages can be rated 5.

Your reply format: ###<number>\*\*\*:

## Pointwise Reranking Phase RAG Prompt

You are a single-number rater. Answer with a single number. You will be given a question and a passage. On a scale of 1 to 5, please evaluate how suitable the passage is for answering the question. The higher the score, the more suitable the passage is for providing answers. A passage that adequately answers a question should be rated 3. A passage that is not at all suitable for answering questions should be rated 1. Passages that provide clear, accurate, and comprehensive answers can be rated 5.

Your reply format: ###<number>\*\*\*..

Question: <question> Passage: <passage>

### Generation Phase

Below you will be given a question and two passages. Please answer the question based on those two passages. Please finish reading both passages before you answer. Your answer must be retrieved from the one of the passages. Answer in the following format:

Answer: <short answer>;

Answer retrieved from which passage: 1 or 2

## **E.2** Passage Examples

# E.2.1 Example of Human, ChatGPT, LLaMA Written Passages

Figure 4 shows an example of human, GPT, and LLaMA authored passages. The figure shows an example of text comparison, highlighting that while the information contained in both model-generated passages mirrors that of the human passage, the style of model-generated text differs from that of human writing.

# E.2.2 Example of Passages of Different Writing Styles

Fig 5 shows passages of different styles generated by language models. At the top, the prompts and instructions are provided for each style. The left passage, "normal passage", maintains a standard, concise structure. The middle passage, "gen-by-qa passage", is generated by answering a question based on the input content. The right passage, "long passage", is a more extended version of the original text, maintaining the same information while expanding its length and adding more details.

#### human passage

### ChatGPT passage

### Llama passage

Bat Out of Hell is the debut studio album by American rock singer Meat Loaf, as well as his first collaboration with composer Jim Steinman and producer Todd Rundgren. The album was released in September 1977 on Cleveland International/Epic Records. It is one of the best-selling albums of all time, having sold over 43 million copies worldwide. "Rolling Stone" "Magazine" ranked it at number 343 on its list of the 500 greatest albums of all time in 2003. Its musical style is influenced by Steinman's appreciation of Richard Wagner, Phil Spector, Bruce Springsteen and The Who..

Bat Out of Hell, the debut studio album by American rock singer Meat Loaf, marked his first collaboration with composer Jim Steinman and producer Todd Rundgren. Released in September 1977 on Cleveland International/Epic Records, the album quickly became a sensation, selling over 43 million copies worldwide and cementing its place as one of the best-selling albums of all time. In 2003, "Rolling Stone" "Magazine" recognized its greatness by ranking it at number 343 on their list of the 500 greatest albums of all time. The musical style of Bat Out of Hell is heavily influenced by Steinman's admiration for Richard Wagner, Phil Spector, Bruce Springsteen, and The Who.

Meat Loaf's Bat Out of Hell, a collaboration with composer Jim Steinman and producer Todd Rundgren, is one of the best-selling albums of all time, with over 43 million copies sold worldwide. Released in September 1977 on Cleveland International/Epic Records, it is the singer's debut studio album. The album's musical style reflects Steinman's admiration for Richard Wagner, Phil Spector, Bruce Springsteen, and The Who, and was ranked 343rd on Rolling Stone Magazine's list of the 500 greatest albums of all time in 2003.

Figure 4: Comparison of passages generated by human, ChatGPT and LLaMA. The left passage comes from a human-generated dataset, the middle and right passages are generated by ChatGPT and LLaMA, respectively.

Please rewrite the following paragraph in You will be given a QA pair. Generate a Please rewrite the following paragraph and make it longer in 100 word passage that can be used to your writing style. The new paragraph your writing style. The new paragraph should contain the same should contain the same information as in answer the question. information as in the original one but the total words must be at the original one Question: <question> least 300. Please ensure that the information doesn't change. Passage: <passage> Answer: <answer> Passage: <passage> question: when did bat out of hell get released answer: September 1977 passage: Bat Out of Hell Bat Out of Hell is the debut studio album by American rock singer Meat Loaf, as well as his first collaboration with composer Jim Steinman and producer Todd Rundgren. The album was released in September 1977 on Cleveland International/Epic Records. It is one of the best-selling albums of all time, having sold over 43 million copies worldwide. "Rolling Stone" "Magazine" ranked it at number 343 on its list of the 500 greatest albums of all time in 2003. Its musical style is influenced by Steinman's appreciation of Richard Wagner, Phil Spector, Bruce Springsteen and The Who. normal passage gen-by-qa passage long passage LLM LLM LLM Bat Out of Hell marked the beginning of an iconic partnership between American rock singer Meat Loaf, composer Jim Steinman, and producer Todd Rundgren. Released in September 1977 under the Cleveland Bat Out of Hell, the debut studio album "Bat Out of Hell," the iconic debut album by American rock singer Meat Loaf. by American rock musician Meat Loaf. marked his first collaboration with was released in September 1977. The International/Epic Records label, this debut studio album quickly became a classic in the rock genre. Its massive success is evident in its impressive composer Jim Steinman and producer album quickly became a commercial Todd Rundgren. Released in September success, making Meat Loaf a household sales figures, with over 43 million copies sold worldwide. The album's 1977 on Cleveland International/Epic name and solidifying his status as a rock music legend. With hits like "Paradise by impact was recognized by "Rolling Stone" magazine, which included it in their prestigious list of the 500 greatest albums of all time, ranking it at Records, the album quickly became a sensation, selling over 43 million copies the Dashboard Light" and the title track number 343 in 2003. The musical brilliance of Bat Out of Hell is a result of the eclectic worldwide and cementing its place as "Bat Out of Hell," the album captured the influences that Steinman drew upon in creating the album. His admiration one of the best-selling albums of all time. In 2003, "Rolling Stone" "Magazine" hearts of music lovers around the world. for the grandeur of Richard Wagner, the wall of sound technique of Phil Spector, the storytelling of Bruce Springsteen, and the raw energy of The Who can be heard in the epic tracks that make up this masterpiece. The Its unique blend of rock, pop, and recognized its greatness by ranking it at theatrical elements continues to resonate number 343 on their list of the 500 with audiences to this day, making it a album's unique blend of rock, opera, and theatricality set it apart from other releases of its time, solidifying its status as a groundbreaking work of art. greatest albums of all time. The musical timeless classic in the rock music genre Meat Loaf's powerful vocals, combined with Steinman's eloquent lyrics and style of Bat Out of Hell is heavily Rundgren's innovative production, resulted in an album that resonated with influenced by Steinman's admiration for audiences around the world. The unforgettable anthems such as "Paradise by the Dashboard Light" and "Two Out of Three Ain't Bad" have become Richard Wagner, Phil Spector, Bruce timeless classics that continue to captivate listeners to this day. Bat Out of Hell's legacy lives on as a testament to the creative genius of its creators Springsteen, and The Who. and its enduring influence on the music industry.

Figure 5: Example of generating different writing style passages.

Dataset	Evaluator	Setting	Factuality	~	Score Distribution				
				Generator	1	2	3	4	5
NQ -	GPT		true	Human	4	6	75	810	97
				GPT	1	1	25	811	162
		Normal		LLaMA	0	2	18	772	208
			false	Human	1	22	115	784	69
				GPT	1	4	30	830	134
				LLaMA	0	3	29	810	157
		RAG	true	Human	21	332	43	567	37
				GPT	12	308	29	627	24
				LLaMA	21	281	44	625	29
			false	Human	33	432	58	467	10
				GPT	22	449	44	475	10
				LLaMA	27	432	50	478	13
	Llama	Normal	true	Human	0	45	206	749	0
				GPT	0	12	60	927	1
				LLaMA	0	8	41	951	0
			false	Human	0	70	231	699	0
				GPT	0	30	75	895	0
				LLaMA	0	17	52	930	1
		RAG	true	Human	6	507	110	331	43
				GPT	6	303	118	484	86
				LLaMA	6	249	126	509	108
			false	Human	8	576	118	261	35
				GPT	9	365	109	451	63
				LLaMA	6	322	103	489	77
MARCO -	GPT	Normal	true	Human	1	18	75	838	50
				GPT	0	2	26	882	87
				LLaMA	0	0	14	841	140
			false	Human	6	31	129	787	31
				GPT	1	9	44	887	57
				LLaMA	0	4	30	862	102
		RAG	true	Human	8	227	103	642	20
				GPT	8	232	71	675	14
				LLaMA	5	262	43	667	23
			false	Human	28	388	104	477	3
				GPT	23	403	86	484	4
				LLaMA	36	406	57	494	7
	Llama	Normal	true	Human	0	110	239	651	0
				GPT	0	23	98	879	0
				LLaMA	0	23	42	935	0
			false	Human	1	173	261	565	0
				GPT LLaMA	0	61 41	118 72	820 887	0
				Human	3	265	185	480	
		RAG -	true	Human GPT	0	203	157	547	66 81
				LLaMA	2	193	137	564	
			false		8	369	164	417	102 42
				Human GPT	8 6	301	152	417	42 57
				LLaMA	6	282	147	493	72
				LLaWIA	O	202	14/	473	12

Table 14: Statistical Distribution of Pointwise Reranking Results