Am I More Pointwise or Pairwise?
Revealing Position Bias in Rubric-Based LLM-as-a-Judge

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Abstract

Large language models (LLMs) are now widely used to evaluate the quality of text, a field commonly referred to as LLM-as-a-judge. While prior works mainly focus on point-wise and pairwise evaluation paradigms. Rubric-based evaluation, where LLMs select a score from multiple rubrics, has received less analysis. In this work, we show that rubric-based evaluation implicitly resembles a multi-choice setting and therefore has position bias: LLMs prefer score options appearing at specific positions in the rubric list. Through controlled experiments across multiple models and datasets, we demonstrate consistent position bias. To mitigate this bias, we propose a balanced permutation strategy that evenly distributes each score option across positions. We show that aggregating scores across balanced permutations not only reveals latent position bias, but also improves correlation between the LLM-as-a-Judge and human. Our results suggest that rubric-based LLM-as-a-Judge is not inherently point-wise and that simple permutation-based calibration can substantially improve its reliability.

1. Introduction

Large language models (LLMs), exemplified by Chat-GPT (OpenAI et al., 2023), have been widely applied to language-related tasks due to their strong performance, such as summarization (Goyal et al., 2022; Bhaskar et al., 2023), question answering (Rein et al., 2024), and even creative idea generation (Lu et al., 2024; Xu et al., 2025). Due to their strong generality on text related tasks, LLMs can also be used to generate evaluations of textual quality, a paradigm commonly referred to as LLM-as-a-Judge (Zheng et al., 2023; Ye et al., 2024; Fu et al., 2024). This capability is useful not only for producing evaluation scores but also for training LLMs themselves (Lee et al., 2024), leading to

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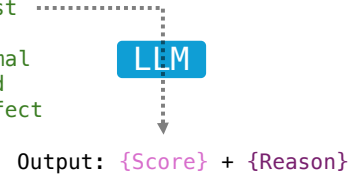[1]OMRON SINIC X [2]NexaScience. Correspondence to: <>.
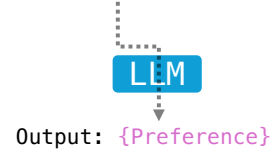
Figure 1. Three paradigms of LLM-as-a-Judge evaluation. Point-wise evaluation assigns a score given a question and a single response. Pair-wise evaluation compares two responses and outputs the model's preference. Rubric-based evaluation further incorporates explicit scoring criteria. Judge models may also exhibit position bias toward responses in certain orders.

a wide range of applications.

Although LLMs are highly capable in this regard, their performance has also been questioned. Some prior work has pointed out that using LLMs as judges for text quality evaluation can introduce various biases like position bias, verbosity bias, and so on (Zheng et al., 2023; Ye et al., 2024; Chen et al., 2024; Huang et al., 2025). This phenomenon needs to be carefully considered in practice.

The presence of bias can also depend on the evaluation type. As shown in Figure 1, in practice, two popular evaluation paradigms are commonly used: point-wise and pairwise (Tripathi et al., 2025). The former assigns a score to a given response, while the latter selects the better one between two candidate responses. Constructing rubrics and asking the model to perform evaluation based on them is
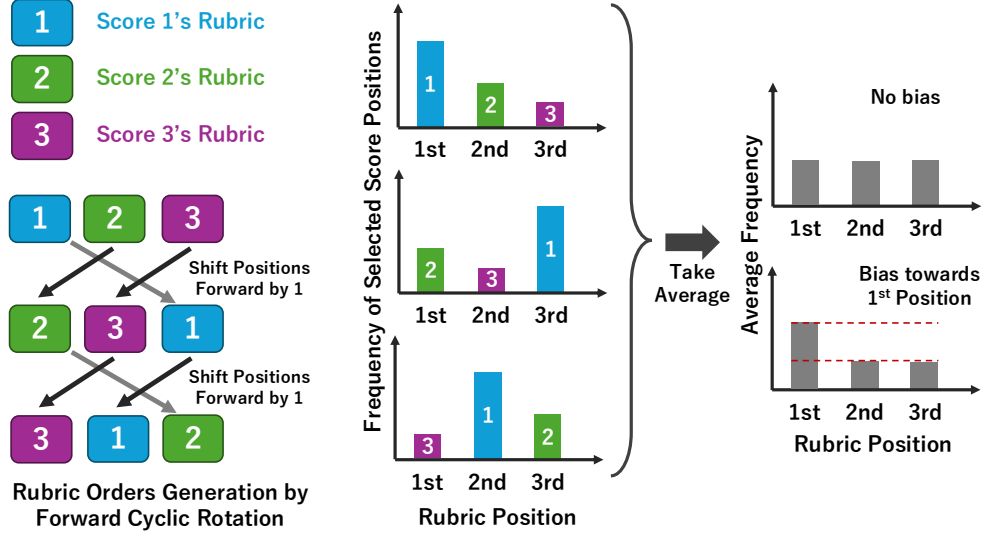
Figure 2. Balanced permutation of rubric orderings. Aggregating the model's choice distributions across permutations marginalizes out score identities and reveals systematic position bias.

also a widely adopted approach (Kim et al., 2024), as it provides greater flexibility.

In this paper, we focus on the rubric-based LLM-as-a-Judge setting. Since there is only a single text to be evaluated, there should be no position bias in the classical sense. However, the rubric-based LLM-as-a-Judge can be viewed as a multiple-choice selection problem: given a text for evaluation, the LLM must choose the rubric option that aligns most with the text. Unlike the pair-wise setting, positional bias in rubric-based evaluation is less salient, because score selections are inherently imbalanced and dominated by the underlying score distribution, making positional effects harder to observe directly.

In our work, inspired by position bias observed in pair-wise evaluation, we propose balanced permutation to disentangle the influence of score values from positional choice preferences in rubric-based LLM-as-a-Judge. By ensuring that each score is evenly distributed across different positions over multiple evaluations, our method enables us to uncover position bias in rubric-based evaluations. Figure 2 illustrates how aggregating model choices across balanced rubric permutations reveals systematic positional preference.

Our contributions are summarized as follows:

- We identify bias in how LLMs handle rubrics: models tend to prefer options appearing at the beginning or the end of the list.

- We show that balanced permutation can also be used to calibrate the correlation between LLM-generated scores and human judgments. This method can serve as

an alternative to conducting multiple evaluation runs.

- We propose a human-annotation-free method for selecting rubric orderings: by performing a small number of probing evaluations to estimate a model's score–position preferences, we define a Bias Cost to quantify the positional deviation of a rubric ordering, and then select a more reliable ordering from candidate permutations.

2. Related Work

LLM-as-a-Judge: Human evaluation of text is an expensive option. With the advent of RLHF (Ouyang et al., 2022), LLMs have acquired a certain degree of alignment with human values, which makes LLM-as-a-Judge feasible (Zheng et al., 2023). Fu et al. (2024) first explored the use of GPT models for evaluating text data. This work addressed a long-standing limitation of traditional evaluation: it's hard to flexibly and easily adapt evaluation criteria to different tasks and requirements. Zheng et al. (2023) systematically studied LLM-as-a-Judge by introducing MT-Bench. Their results show that strong models used as LLM-as-a-Judge can closely match human preferences, achieving over 80% agreement. Such a high level of agreement enables LLMs to be used even for training other LLMs, achieving performance comparable to RLHF. This approach is known as RLAIF (Lee et al., 2024).

Our work is positioned within the line of research on LLM-as-a-Judge and focuses on a previously underexplored issue in rubric-based evaluation. We identify position bias induced by rubric ordering and propose a simple, model-

agnostic mitigation strategy.

Evaluation Biases: Similar to humans (Chen et al., 2024), LLM-as-a-Judge also exhibits biases. A notable example is position bias: in a pair-wise evaluation setting, the model may tend to prefer either the first or the second response, depending on factors such as the model's capability and the quality of the answers. This bias can be mitigated by swapping the order and performing evaluation twice (Zheng et al., 2023). LLMs also show length bias, tending to assign higher scores to longer, more verbose responses (Zheng et al., 2023; Tripathi et al., 2025). Shi et al. (2025) argue that the quality gap between candidate responses has a significant impact on position bias, while length difference is not. In addition, an LLM may favor outputs generated by itself or by closely related models (Chen et al., 2025b;a; Zheng et al., 2023). Wataoka et al. (2024) explain this phenomenon by noting that LLMs tend to prefer responses with lower perplexity, and outputs generated by the same model or closely related models often have relatively lower perplexity. Related to our work, Li et al. (2025) shows that different rubric orderings can affect the correlation between LLMs and human scores. We extend this line of work by explicitly framing this phenomenon as position bias and by proposing a balanced permutation scheme that both reveals and mitigates it.

3. Problem Formulation and Methods

Our work aims to study whether LLMs suffer from position bias in the rubric-based format. In this setting, an LLM is asked to judge a question-response pair with a set of rubric score options. We define position bias in this context as a systematic preference for selecting score options appearing at particular positions.

3.1. Balanced Permutation

In studies of position bias in pair-wise evaluation, a common mitigation is to swap the two responses to cancel out the effect. In the rubric-based setting, however, we have multiple score options, which makes a simple swap ineffective. Nevertheless, as long as we can ensure that each score appears equally often at each position, we can in principle factor out the influence introduced by the score values themselves.

To address this, we propose a balanced permutation method. The key insight is that position bias can be neutralized if each score option appears in each position an equal number of times across multiple evaluation runs. Specifically, we construct 10 complementary orderings: 5 forward cyclic rotations ([1,2,3,4,5], [2,3,4,5,1], ...) and 5 reverse cyclic rotations ([5,4,3,2,1], [4,3,2,1,5], ...). This design ensures that every score appears exactly twice in each position, effectively canceling out any systematic positional preference

while preserving the semantic signal of the scores.

4. Experimental Setup

We evaluated position bias using five models across four datasets. Two of these datasets include human ratings, which allowed us to compute the correlation between LLM scores and human judgments under the permutation-based setting.

4.1. Datasets

Table 1. Dataset Statistics

Dataset	Composition	Total
MT-Bench	80 prompts × 4 models	320
Vicuna-Bench	80 prompts × 4 models	320
HANNA	96 stories × 6 criteria	576
SummEval	100 articles × 4 models × 4 criteria	1,600
Total		**2,816**

We use MT Bench, HANNA, and SummEval, and Vicuna Bench as our datasets for evaluation. Our data are either taken from Kim et al. (2024) or adapted following their format, and therefore differ from those used in the original paper. Detailed description of the dataset are outlined below:

- **MT Bench** (Zheng et al., 2023): A multi-turn conversation dataset with 80 prompts across 8 categories (writing, roleplay, reasoning, math, coding, extraction, STEM, humanities). ChatGPT (OpenAI et al., 2023), Llama-2-Chat-13B (Touvron et al., 2023), Vicuna-13B (Chiang et al., 2023), and WizardLM-13B (Xu et al., 2024) were used to generate responses, resulting in a total of 320 responses.

- **Vicuna Bench** (Chiang et al., 2023): A single-turn conversation benchmark with 80 prompts across 9 categories (generic, knowledge, roleplay, common-sense, fermi, counterfactual, coding, math, writing). Similar to MT Bench, it has 320 responses from 4 models.

- **HANNA** (Chhun et al., 2024): A story generation benchmark. We use a subset of 96 stories written by humans across 6 criteria (Coherence, Empathy, Surprise, Engagement, Relevance, Complexity). Each evaluation is annotated by 3 human raters.

- **SummEval** (Fabbri et al., 2021): A summarization evaluation benchmark with 100 CNN/DailyMail articles, each summarized by 4 models on 4 criteria (coherence, consistency, fluency, relevance). Each evaluation is made by 3 human expert raters.

4.2. Judge Models

We evaluate position bias using GPT-4.1 and GPT-4.1-mini (OpenAI, 2024), Qwen3-8B and Qwen3-32B (Yang et al., 2025), as well as GPT-OSS-120B (OpenAI et al., 2025). Among these models, Qwen3 and the gpt oss model support a reasoning mode. For Qwen3, we evaluate performance with reasoning both disabled and enabled, while for the gpt oss model we keep reasoning enabled throughout. For the temperature setting, we use temperature 0 for all models except Qwen3 in reasoning mode, where we set the temperature to 0.3. We adopt 0.3 to mitigate an issue we encountered in which the model could fall into repetitive loops and generate indefinitely repeated outputs; using a nonzero temperature helps alleviate this behavior.

4.3. LLM Instructions

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###Task Description:
An instruction (might include an Input
inside it), a response to evaluate, [a
reference answer that gets a score of 5,]
and a score rubric representing an
evaluation criterion are given.
1. Write a detailed feedback that
assesses the quality of the response
strictly based on the given score rubric,
not evaluating in general.
2. After writing a feedback, write a
score that is an integer between 1 and 5.
You should refer to the score rubric.
3. The output format should look as
follows: "Feedback: (write a feedback for
criteria) [RESULT] (an integer number
between 1 and 5)"
4. Please do not generate any other
opening, closing, and explanations.

###The instruction to evaluate:
{instruction}

###Response to evaluate:
{response}

###Reference Answer (Score 5):
{reference}

###Score Rubrics:
[{criterion_name}]
Score 1: {description_1}
Score 2: {description_2}
Score 3: {description_3}
Score 4: {description_4}
Score 5: {description_5}

###Feedback:
```

Figure 3. Unified prompt format used in all experiments (Prometheus-Eval).

Figure 3 illustrates the prompt template used in our experiments, which basically follows the style in Kim et al. (2024). The LLM is provided with a task description, the instruction to evaluate, the response, a reference answer, and line-by-line score rubrics, and is asked to produce written feedback and a score from 1 to 5. Note that the HANNA and SummEval datasets do not include a reference answer in the prompt.

4.4. Evaluation Protocol

We apply the balanced permutation scheme in Section 3.1 by varying the rubric ordering for each instance, as shown in Figure 4.
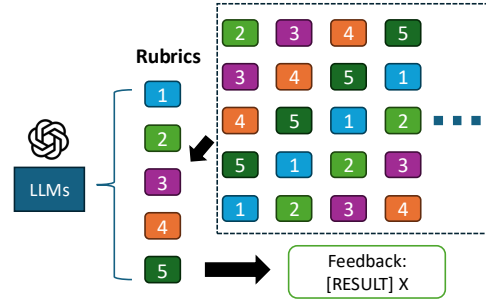

Figure 4. An illustration of balanced permutations of rubric scores, ensuring that each score appears equally often at each position.

Through experiments with balanced permutations, we can confirm the existence of position bias. We also want to examine whether balanced permutation can reduce the impact of this bias. A straightforward approach is to average the scores across permutations; since the correct score should appear equally often at each position, averaging should in principle cancel out positional effects. In our experiments, we use ten permutations and compare the average score over these ten permutations with the score obtained by directly averaging the ten individual predictions. Because the labels for MT Bench and Vicuna are also derived from GPT outputs and thus may themselves contain position bias, we only report results on HANNA and SummEval, which provide human annotations.

4.5. Metrics

We evaluate alignment between LLM judge scores and human annotations using Pearson's correlation coefficient r and Spearman's rank correlation coefficient ρ.

5. Results

5.1. Position Bias

As shown in Figure 5, we observe position bias across all models. This indicates that even when scores are evenly distributed across positions, the models do not select the
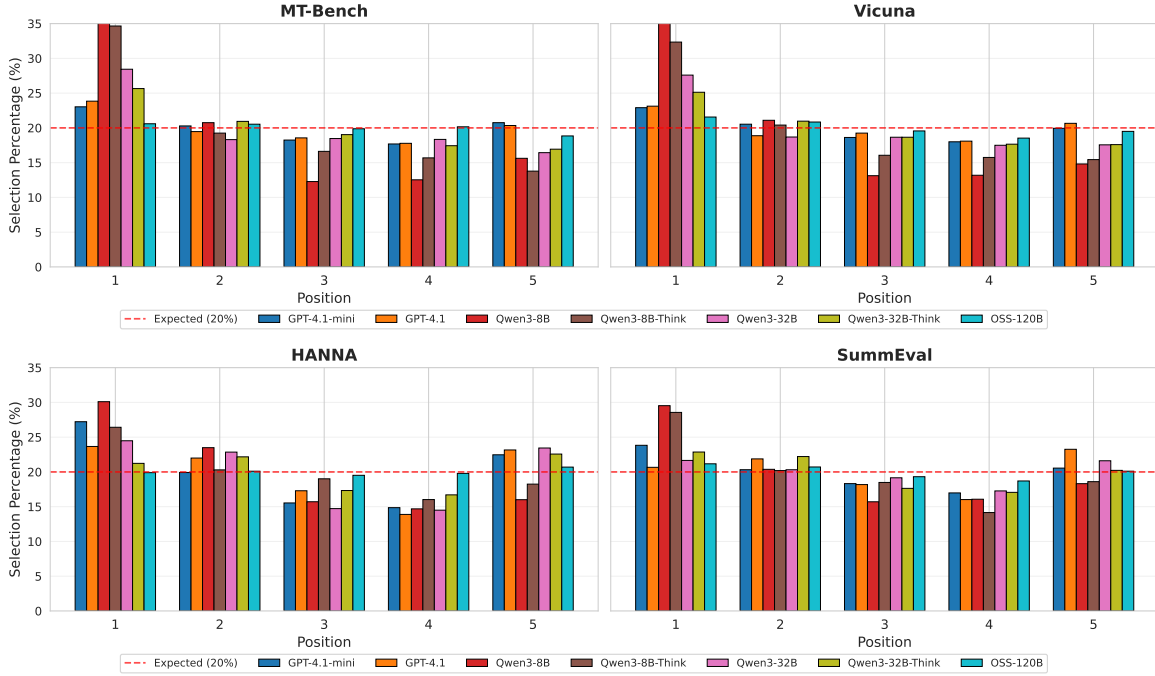
Figure 5. Position selection distribution on 4 datasets. The dashed red line indicates the expected 20% baseline under no position bias.

correct score at each position uniformly. All models exhibit a consistent preference for the first position.

The severity of the position bias varies largely across models. Smaller models show stronger bias: Qwen3-8B selects Position 1 in about 30–39% of cases, while larger models like GPT-4.1 and OSS-120B show a more ideal distribution. Notably, the bias pattern is consistent across all four datasets, suggesting this is an inherent model characteristic rather than a task-specific artifact.

The patterns we observe are similar to those reported in Lost in the Middle (Liu et al., 2023): the models exhibit primacy and recency biases, with LLMs selecting score options at the beginning and the end of the list more frequently.

5.2. Balanced Permutation

The balanced permutation method not only reveals this position bias, but can also, in principle, be used to mitigate it. The correlations between model and human scores for with and without permutation are shown in Table 2. We also report within-item standard deviation (σ) in Table 3, measuring prediction consistency across 10 trials. Permutation naturally yields higher variance due to varying rubric orderings. In addition, for models with reasoning enabled, the deviation is higher because we set the temperature to 0.3. However, higher deviation alone does not necessarily lead to improved correlation.

Table 2 compares human correlation results between using

ten different rubric permutations (Permutation) and repeating a fixed ordering ten times (Repeat). Overall, the Permutation approach outperforms the Repeat baseline, indicating that diversifying rubric orderings can effectively mitigate the impact of position bias on evaluation quality.

More specifically, GPT series models (GPT-4.1-mini and GPT-4.1) show consistent improvements across both datasets, with GPT-4.1 achieving the most notable gain on the HANNA dataset, where the Spearman correlation increases by +0.041. The largest improvements are observed for Qwen3-32B and Qwen3-32B-Think, particularly on HANNA, with Spearman correlations improving by 0.089 and 0.082, respectively. This suggests that for models exhibiting stronger position bias, the Permutation method provides more substantial mitigation benefits. In addition, we find that GPT-OSS-120B, which exhibits the smallest position bias, does not outperform GPT-4.1 or GPT-4.1-mini. This suggests that lower position bias does not necessarily translate into better overall performance.

Notably, Qwen3-8B is the only model for which Permutation performs worse than Repeat. This suggests that removing position bias does not necessarily improve performance, because under certain model preferences and dataset distributions, a particular ordering may yield better results than a bias-corrected setting. To show this, we also analyze the correlation of each of the ten individual permutations separately (noting that, in this case, the correlation is computed using data that are evaluated only once). As shown in Table 4,

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Table 2. Comparison of 10-ordering permutation vs 10-repeat (fixed ordering) on human correlation. Δ shows the improvement from permutation. Bold indicates better performance between the two methods.

Model	HANNA						SummEval					
	Pearson r			Spearman ρ			Pearson r			Spearman ρ		
	Perm	Rep	Δ	Perm	Rep	Δ	Perm	Rep	Δ	Perm	Rep	Δ
GPT-4.1-mini	**.446**	.415	+.031	**.449**	.427	+.022	**.444**	.433	+.011	**.387**	.383	+.005
GPT-4.1	**.464**	.433	+.032	**.481**	.440	+.041	**.460**	.429	+.031	**.405**	.372	+.033
Qwen3-8B	.332	**.378**	-.046	.324	**.376**	-.052	.388	.388	.000	.357	**.372**	-.015
Qwen3-8B-Think	**.378**	.349	+.030	**.358**	.339	+.019	**.440**	.415	+.025	**.394**	.390	+.004
Qwen3-32B	**.369**	.303	+.066	**.309**	.220	+.089	**.431**	.394	+.037	**.412**	.363	+.050
Qwen3-32B-Think	**.347**	.289	+.058	**.310**	.228	+.082	**.414**	.395	+.019	**.362**	.351	+.011
OSS-120B	**.393**	.375	+.018	**.380**	.358	+.021	.408	**.410**	-.001	**.354**	.345	+.010
Average	**.390**	.363	+.027	**.373**	.341	+.032	**.427**	.409	+.018	**.382**	.368	+.014

Table 3. Within-item standard deviation (σ) of predicted scores across 10 trials. Lower values indicate more consistent predictions. Permutation uses 10 different rubric orderings; Repeat uses fixed ordering with 10 repetitions.

Model	HANNA		SummEval	
	Perm	Rep	Perm	Rep
GPT-4.1-mini	0.501	0.277	0.296	0.160
GPT-4.1	0.475	0.204	0.331	0.138
Qwen3-8B	0.553	0.118	0.419	0.043
Qwen3-8B-Think	0.520	0.469	0.486	0.395
Qwen3-32B	0.594	0.118	0.355	0.039
Qwen3-32B-Think	0.545	0.500	0.467	0.426
OSS-120B	0.411	0.281	0.280	0.188

the 12345 ordering achieves the highest correlation ranking (1/10) for Qwen3-8B. That's why it can not be improved by the balanced permutation. In contrast, Qwen3-32B starts with lower correlation (5/10) under the 12345 ordering but benefits from permutation averaging. Overall, eliminating position bias does not necessarily improve a model's performance on a specific benchmark, since in some cases biased predictions exhibit higher correlation with the ground truth.

5.3. Score-Positon Interaction

As shown in Table 5, we compute, for each model across all datasets, the probability that a given score is selected at each position. We observe that for almost all scores, the highest selection probabilities concentrate at Positions 1, 2, and 5. Ideally, the probability at each position would be 20%. However, given that position bias is likely rooted in model architecture rather than data characteristics (Liu et al., 2023), this issue is difficult to eliminate entirely.

In scenarios where human ground-truth annotations are unavailable and we wish to avoid simply averaging over multiple permutations, a natural question arises: how can we obtain an ordering that yields the highest possible correlation? We propose to first probe the model using a small set of rubric orderings, collecting statistics similar to those in Table 5 to estimate score selection bias. Based on these statistics, we define a *Bias Cost* to quantify positional deviation.

For a permutation $\pi = [\pi_1, \pi_2, \pi_3, \pi_4, \pi_5]$, where Position p is assigned Score π_p, the Bias Cost is defined as:

$$\text{Cost}(\pi) = \sum_{p=1}^{5} |P(p \mid \pi_p) - 0.2|.$$

We expect that a lower *Bias Cost* will lead to higher correlation. As shown in Table 6, we compute the Bias Cost for the ten different rubric orderings in our existing data. In most cases, the ordering with the lowest Bias Cost ranks within the top 50% in terms of correlation, suggesting that this method is effective.

6. Discussion

In this work, we reveal position bias in rubric-based LLM-as-a-Judge settings. Similar to the phenomenon described in Lost in the Middle (Liu et al., 2023), LLMs exhibit primacy and recency effects, with score options at the beginning and the end of the list being selected more frequently. By applying our balanced permutation method, we are able to reduce the impact of position bias on scoring. However, due to the inherent distribution of score values, eliminating position bias does not necessarily lead to improved correlation.

In addition, we find that arranging rubric orderings such that each score's selection probability is as close as possible to 20% can yield relatively high correlation. This provides a practical alternative in scenarios where human ground truth is unavailable and large-scale computation is infeasible.

7. Limitations and Future Work

The number of possible permutations is large; however, due to computational constraints, we only evaluate ten of

Table 4. [1,2,3,4,5] ordering rank among 10 orderings for each dataset. Rank 1 means [1,2,3,4,5] has the highest Pearson correlation; Rank 10 means the lowest.

Model	HANNA			SummEval		
	[1..5]	Avg	Rank	[1..5]	Avg	Rank
GPT-4.1-mini	0.384	0.382	5/10	0.415	0.407	3/10
GPT-4.1	0.411	0.405	6/10	0.412	0.419	9/10
Qwen3-8B	**0.350**	0.295	**1/10**	**0.387**	0.330	**1/10**
Qwen3-8B-Think	0.328	0.317	4/10	0.355	0.358	6/10
Qwen3-32B	0.299	0.313	5/10	0.388	0.385	4/10
Qwen3-32B-Think	0.205	0.279	**10/10**	0.322	0.346	9/10
OSS-120B	0.357	0.363	6/10	0.388	0.385	4/10

Table 5. Score Selection Distribution by Position (%). For each score, the distribution of its selections across positions. If no position bias exists, all values in a row should be 20.

Models (1–4)							Models (5–7)						
Model	Score	P1	P2	P3	P4	P5	Model	Score	P1	P2	P3	P4	P5
GPT-4.1-mini	1	27.9	17.5	15.9	14.9	23.8	Qwen3-32B	1	21.4	19.1	19.2	21.5	18.8
	2	28.5	18.7	16.3	17.8	18.7		2	29.4	19.2	18.5	19.0	13.9
	3	23.9	19.1	19.2	17.8	20.1		3	24.4	19.9	18.2	16.1	21.4
	4	24.7	19.2	17.5	16.7	21.9		4	18.7	18.1	19.9	18.2	25.1
	5	24.0	26.8	15.5	12.0	21.7		5	21.3	33.1	11.8	10.1	23.7
GPT-4.1	1	22.7	25.5	15.9	15.9	20.1	Qwen3-32B-Think	1	19.3	19.9	18.0	20.8	22.0
	2	27.4	21.0	16.0	17.3	18.2		2	29.1	22.2	16.0	16.6	16.1
	3	22.2	20.9	18.9	16.1	22.0		3	23.5	20.9	18.2	18.3	19.2
	4	21.1	19.7	18.4	16.6	24.3		4	22.1	20.9	17.5	16.6	22.9
	5	18.4	28.0	16.7	11.5	25.3		5	19.4	26.3	17.2	15.3	21.7
Qwen3-8B	1	19.5	30.2	17.2	15.2	17.9	OSS-120B	1	26.1	18.0	13.5	20.1	22.2
	2	30.1	20.2	14.2	17.5	18.0		2	20.1	20.3	20.4	20.0	19.2
	3	27.4	21.2	16.9	16.9	17.6		3	21.9	21.5	17.9	17.6	21.2
	4	35.0	17.6	15.3	14.5	17.5		4	20.1	19.2	20.7	19.4	20.6
	5	30.3	30.4	12.7	8.8	17.8		5	20.3	21.3	19.5	19.5	19.3
Qwen3-8B-Think	1	24.4	24.4	17.2	16.0	18.1							
	2	30.4	18.6	18.0	17.7	15.2							
	3	26.9	20.4	19.5	15.0	18.2							
	4	29.4	18.6	18.6	14.4	19.0							
	5	26.3	24.7	16.5	12.4	20.1							

Table 6. Min-bias ordering analysis within 10 cyclic rotations. Cost = $\sum_s |P(\text{pos}|s) - 20\%|$; lower = less bias. Corr Rank = Pearson correlation ranking among 10 orderings, averaged across HANNA and SummEval (1 = best, 10 = worst).

Model	Min-Bias Order	Bias Cost		Corr Rank	
		Min-Bias	Default	Min-Bias	Default
GPT-4.1-mini	[5,4,3,2,1]	11.7	15.0	5/10	4/10
GPT-4.1	[5,4,3,2,1]	5.8	13.6	3/10	7/10
Qwen3-8B	[1,2,3,4,5]	11.5	11.5	**1/10**	**1/10**
Qwen3-8B-Think	[1,2,3,4,5]	12.0	12.0	4/10	4/10
Qwen3-32B	[5,4,3,2,1]	7.2	9.5	9/10	6/10
Qwen3-32B-Think	[5,4,3,2,1]	8.7	9.8	2/10	10/10
OSS-120B	[4,3,2,1,5]	2.9	9.8	4/10	5/10

them and still obtain positive results. Evaluating on more diverse datasets would also be beneficial, especially those with substantially different score distributions.

For future work, we believe our approach could also be used to detect whether examinees rely on LLMs to complete assessments on their behalf. By providing specific rubric orderings, we can to some extent manipulate the score outputs produced by LLMs. If a user's final answers are biased toward such outputs, it may indicate the use of an LLM. Although users could in principle counteract this by carefully adjusting the rubrics, doing so would require additional effort. In addition, some work uses rubrics as training signals (Gunjal et al., 2025), and we hypothesize that permuting the order of training rubrics may also improve training stability.

Impact Statement

This work studies the impact of rubric ordering in rubric-based LLM-as-a-Judge evaluation. While our proposed method can reduce position bias in this setting, it could also be misused to manipulate evaluation outcomes if applied deliberately. Therefore, we believe that increasing the transparency of rubrics is an important direction for future research.

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