

# A Human-AI Comparative Analysis of Prompt Sensitivity in LLM-Based Relevance Judgment

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## Abstract

Large Language Models (LLMs) are increasingly used to automate relevance judgments for information retrieval (IR) tasks, often demonstrating agreement with human labels that approaches inter-human agreement. To assess the robustness and reliability of LLM-based relevance judgments, we systematically investigate impact of prompt sensitivity on the task. We collected prompts for relevance assessment from 15 human experts and 15 LLMs across three tasks – binary, graded, and pairwise – yielding 90 prompts in total. After filtering out unusable prompts from three humans and three LLMs, we employed the remaining 72 prompts with three different LLMs as judges to label document/query pairs from two TREC Deep Learning Datasets (2020 and 2021). We compare LLM-generated labels with TREC official human labels using Cohen’s  $\kappa$  and pairwise agreement measures. In addition to investigating the impact of prompt variations on agreement with human labels, we compare human- and LLM-generated prompts and analyze differences among different LLMs as judges. We also compare human- and LLM-generated prompts with the standard UMBRELA prompt used for relevance assessment by Bing and TREC 2024 Retrieval Augmented Generation (RAG) Track. To support future research in LLM-based evaluation, we release all data and prompts at <https://github.com/Narabzad/prompt-sensitivity-relevance-judgements/>.

## CCS Concepts

- Information systems → Evaluation of retrieval results; Relevance assessment; Test collections.

## Keywords

Large Language Models, Relevance Judgments, Evaluation

## 1 Introduction

Large Language Models (LLMs) are increasingly used for evaluation across various domains, including natural language processing and automated content assessment [1, 4, 9, 11, 28, 32]. The information retrieval (IR) community has been an early adopter of LLMs for relevance assessment [19, 24, 27, 35, 41]. Numerous studies have

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confirmed that LLM-generated relevance labels closely align with human labels under multiple measures of agreement [26, 36, 37].

Nonetheless, despite the widespread adoption of LLMs for relevance assessment, prompting strategies vary substantially across studies [2, 3, 20, 33]. An experiment reported at the LLM4Eval Workshop in SIGIR 2024 on Large Language Models for Evaluation in Information Retrieval [29], analyzed how different prompts influence agreement with human judgments and system rankings [28]. While multiple studies have examined how LLMs respond to different prompting strategies [5, 10, 23, 25, 34], these studies have generally been conducted with prompts tuned to specific LLMs and collections, or where prompt variants are constrained by templates [6]. As a complement to these studies, we report on a study of prompts from a variety of independent sources that have not been tuned to LLMs or collections, allowing us to examine the robustness of LLM-based relevance assessment under different prompting strategies. This investigation also allows us to compare different LLMs as judges to determine the degree to which different LLMs are sensitive to prompt modifications.

We collected and analyzed prompts generated by both human experts and LLMs themselves. We designed a guideline for prompting LLMs to perform relevance assessment following three different approaches: *binary*, *graded*, and *pairwise*. While most previous studies have focused on graded relevance, we believe it is crucial to explore a wider range of relevance assessment methods, as they have proven effective in assessing different scenarios in the evaluation of information-seeking systems [7, 8, 13–15, 21, 22, 31, 38–40]. As a benefit to employing LLMs for relevance assessment, it becomes easier to explore different approaches to relevance assessment since human judges do not need to be recruited and trained separately for each approach.

We recruited 15 human participants to create prompts for each of the three assessment approaches. As part of the recruitment process, we ensured that the participants were familiar with prompt engineering and relevance assessment principles, as detailed in Section 2. As a result of this inclusion criteria for recruitment, most participants were drawn from three academia NLP/IR labs. We also collected prompts from 15 different open source and commercial LLMs. Our primary goal is to understand prompt sensitivity in LLM-based relevance judgment [30], including its impact, robustness, and variation across different LLMs. Additionally, we explore the effectiveness of LLM as prompt generators.

We performed relevance judgment experiments using data from two years of the TREC Deep Learning Track: DL 2020 [16], and DL 2021 [17]. Using the prompts created by both human participants and LLMs, we conducted relevance assessments on query-document pairs from these datasets using two open-source LLMs – LLaMA

3.2-3b and Mistral 7b – and one commercial LLM GPT-4o. Our experiment incorporates the three approaches to relevance assessment (binary, graded, and pairwise) with prompts from both humans and LLMs using three different LLMs as judges. Through our experiments, we address the following research questions:

- **RQ1. Impact of Prompts on LLM-based Relevance Judgment Approaches:** Given a clear task objective, how do different prompts influence the effectiveness of each approach to LLM-based relevance judgment?
- **RQ2. LLMs as Prompt Generators:** How effective are LLM-generated prompts for relevance judgment, and how do they compare to human-crafted prompts?
- **RQ3. Prompt Robustness Across LLMs:** Are there prompts that consistently perform well across different LLMs, regardless of the model used as a judge?
- **RQ4. Model-Specific Sensitivity to Prompts:** Is prompt sensitivity consistent across all models, or do some LLMs show greater variability in performance?

To ensure reproducibility, we have made all data and experimental artifacts publicly available at <https://github.com/Narabzad/prompt-sensitivity-relevance-judgements/>. The study reported in this paper, and its associated data release, has received ethics clearance as human subjects research from our institution.

## 2 Prompt Creation

### 2.1 Prompt generation

To investigate the impact of prompting on LLM-based relevance judgment, we collected data from both human participants and LLMs, ensuring that the task objective remained clear and consistent (sharing the same intent) across all participants. We prepared guidelines for prompt writing<sup>1</sup>, which provides detailed explanations of the three relevance judgment tasks: 1) Binary relevance – a passage is either relevant (1) or not relevant (0) to a query. 2) Graded relevance – a passage is rated on a 0-3 scale, where 3 indicates perfect relevance to the query. 3) Pairwise relevance – given two passages, chose the passage more relevant to the query. In the guideline, each task is illustrated with examples from the TREC Deep Learning 2019 [18], helping to ensure that both humans and LLMs had a well-defined understanding of the task. These examples could also be used as (few shot) examples if desired.

The guidelines specify a Python-based format, where participants (both human and LLMs) were required to fill in structured Python dictionaries. More specifically, participants had to provide both the "system message" and "user message" fields for the prompts, following the format commonly used in LLM-based prompting (e.g., OpenAI models and open-source alternatives such as those from Ollama). This structured approach ensures compatibility across different LLM implementations.

We recruited 15 human participants, each of whom had at least a Master's degree in computer science, were fluent in English, and had prior experience working with LLMs via API usage or coding. Additionally, these participants had previously published at least one paper in an IR-focused conference. Each participant received a \$10 gift card as a token of appreciation for their time and effort.

<sup>1</sup><https://bit.ly/4hP0EMg>

**Table 1: List of LLMs used for prompt generation.**

GPT-4o	GPT-4o Mini	Claude 3.5	LLaMA 3.2	Phi-4
Mistral-large	DeepSeek-v3	Amazon-Nova-Pro-v1	Gemma-2-9b	Grok-2
Gemini 2	Jamba-1.5	Athene-v2	GPT01	GPT01 Mini

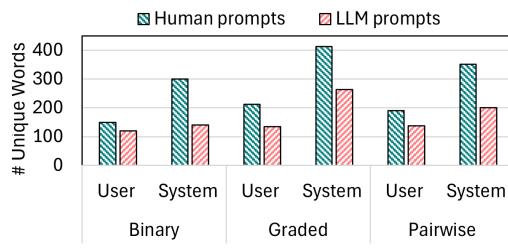
For prompt creation, we also used 15 different LLMs from the ChatBotArena<sup>2</sup> platform [12], which enables the execution of various LLMs online. We provided the same data collection guideline to the LLMs, including the task description and examples, ensuring that the LLMs received identical instructions to those given to human participants. Similar to human participants, each LLM was asked to complete the "system message" and "user message" fields in our Python function for relevance judgment. This setup allow us to systematically compare the impact of prompting across both groups. Table 1 provides the list of LLMs we used in this experiment for generating prompts for relevance judgments.

### 2.2 Filtering and cleaning

To maintain consistency, we did not modify or provide additional instructions for any LLMs or human participants. Among the LLMs, two failed to complete the task because they deemed the task to be inappropriate, or repeatedly asked about examples. Among human participants, only one used a few-shot approach with examples. The rest did not provide any examples in their prompts. When testing the outputs of the collected prompts, not all of them were able to generate the expected format cleanly. Some prompts produced responses that required additional cleaning, such as verbose outputs like "*The passage is relevant, so the answer is: 1*" instead of simply returning 1. To ensure consistency, we examined the all generated output and applied necessary cleaning. After filtering and cleaning, we finalized 12 human-generated prompts and 12 LLM-generated prompts for use in our experiments.

### 2.3 Prompt Diversity

To better understand the variation in prompts, we examined the diversity of both human-generated and LLM-generated prompts. Specifically, we analyzed both *user prompts* and *system prompts* separately, as they serve distinct roles in guiding the LLM's response. In a prompt the user message provides the direct instructions given to the model, specifying what information is needed. In contrast, the system message provides context for the task, defining the LLM's role and expected behavior (e.g., "You are an expert relevance judgment assessor"). Figure 1 illustrates the distribution of unique terms used across all human-generated (in green) and LLM-generated (in red) prompts. As shown in this figure, human-generated prompts exhibit greater diversity in wording when compared to LLM-generated ones. This suggests that humans introduce more nuanced descriptions and varied phrasing when defining the task, while LLM-generated system prompts tend to rely on more standardized language. Additionally, system messages exhibit greater lexical diversity compared to user messages.



**Figure 1: Diversity of words across human and LLM-generated prompts.**

### 3 Experimental Methodology

**Data** We utilize the TREC Deep Learning Track datasets from 2020 and 2021. The DL-20 dataset contains 54 judged queries with 11,386 relevance assessments from MS MARCO V1 collection, while the DL-21 dataset includes 53 judged queries and 10,828 assessments from MS MARCO V2. Both datasets have been manually annotated by NIST assessors following the TREC relevance judgment guidelines. The assessors evaluate each document-query pair based on a graded relevance scale, ranging from not relevant (0) to highly relevant (3). The assessment process involves pooling top-ranked documents from multiple retrieval systems, which were then judged by human annotators. Using this data allows us to compare the three different variations of LLM-based judgments i.e., binary, graded, and pairwise. For graded relevance, we compare against the actual graded labels. For binary judgments, following prior work [19, 37], we classify levels 2 and 3 as relevant and levels 0 and 1 as non-relevant. For pairwise judgments, we compare documents with different relevance levels, assuming that a document with a higher relevance level should be ranked as more relevant than one with a lower relevance level.

**LLMs for Relevance Judgments.** To perform relevance assessment, we employed three different LLMs: one commercial model, GPT-4o, and two open-source models, LLaMA 3.2-3B and Mistral-7B<sup>2</sup>. We implemented our experiments using OpenAI and Ollama, running all prompts with a temperature setting of 0.

**Data Sampling.** We conducted experiments on all query-document pairs for binary and graded relevance judgments using the open-source models. However, due to computational constraints, we were unable to run all 24 valid prompts across all query-document pairs for GPT-4o. Instead, we randomly sampled up to 10 documents per query for each of the four relevance levels (0-3). If fewer than 10 documents were available for a given relevance level, we included all available documents. For pairwise judgments, evaluating all possible pairs was not feasible due to their quadratic growth. Instead, we categorized documents for each query into three groups: “highly relevant”, “relevant”, and “non-relevant”. The “highly relevant” category corresponds to the highest available relevance level for that query, which in TREC-style annotations could be level 3 or level 2, depending on availability. The “non-relevant” category includes all level 0 documents, while any intermediate relevance level (typically level 1, or levels 1 and 2 if level 3 exists) was classified as “relevant”.

<sup>2</sup><https://lmarena.ai/>

**Table 2: Mean and variance of agreement between LLM-based and human relevance judgments across different settings.**

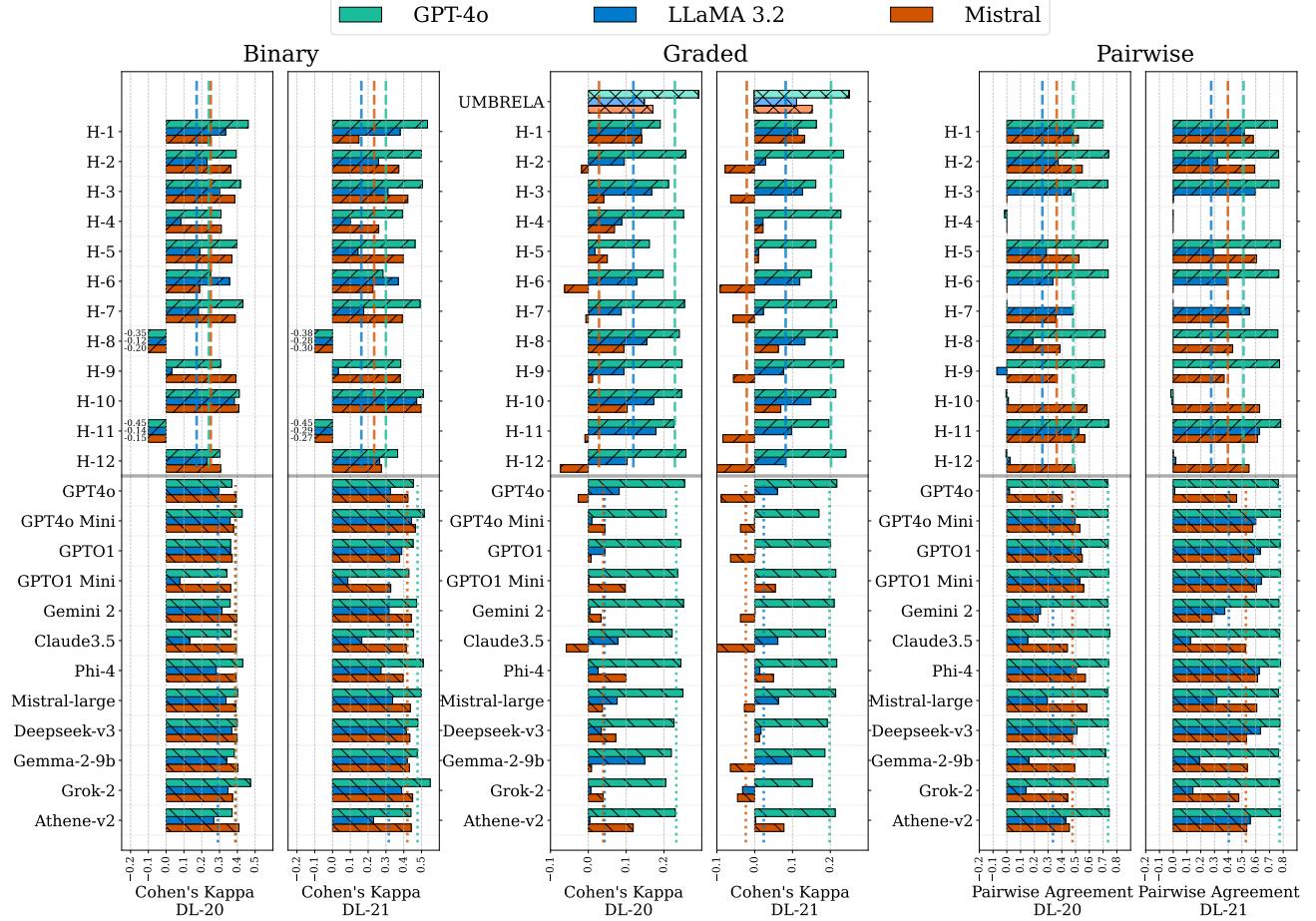
Model	crafted by	Binary		Graded		Pairwise	
		Mean	Variance	Mean	Variance	Mean	Variance
GPT-4o	LLM	0.434	0.003	0.215	0.001	0.849	0.000
	Human	0.270	0.098	0.215	0.001	0.578	0.139
LLaMA 3.2	LLM	0.303	0.010	0.033	0.002	0.439	0.066
	Human	0.167	0.041	0.102	0.003	0.330	0.073
Mistral	LLM	0.405	0.001	0.008	0.004	0.574	0.014
	Human	0.243	0.051	0.004	0.005	0.442	0.073

From these three categories, we constructed document pairs for pairwise judgments. Specifically, we sampled 10 pairs per query from each of the following comparisons: “highly relevant vs. non-relevant”, “relevant vs. non-relevant”, and “highly relevant vs. relevant” (up to 30 pairs in total). If fewer than 10 pairs were available for a given comparison, we included as many as possible. Additionally, for the pairwise setting, we minimized positional bias by evaluating each document pair twice, swapping the order of the documents in the second run. The result is counted as “agree” if the LLM favors the more relevant passage in both comparisons, “tie” if the LLM’s decisions are inconsistent when the passage order is swapped, and “disagree” if the LLM consistently selects the passage with a lower relevance level assigned by human annotators.

### 4 Results and Findings

In order to explore the research questions raised in the introduction, we investigated the agreement of LLM-based relevance judgments from different prompts with human annotations on TREC 2020 and 2021 using three different LLMs, as shown in Figure 2. For binary and graded relevance judgments, agreement is measured using Cohen’s Kappa ( $\kappa$ ). For pairwise judgments, since the task involves assessing agreement with the actual ranking of pairs, we report the percentage of cases where the LLM’s preference agrees with the expected order. In this figure, the leftmost two columns represent the results for binary, the middle two columns correspond to graded, and the rightmost two columns display the results from pairwise relevance judgment. The green, blue, and red bars indicate agreement for GPT-4o, LLaMA 3.2, and Mistral, respectively. In each pair of plots, the left plot presents results for DL-20, while the right plot corresponds to DL-21. The bottom 12 bars represent prompts crafted by LLMs; on top of them there are 12 bars corresponding to prompts created by humans.

In addition to results from the human- and LLM-written prompts, we also report the results of UMBRELA assessments at the top of the graded relevance sub-figure (middle). UMBRELA is an open-source reproduction of Microsoft’s Bing LLM-based relevance assessor [35], designed to automate relevance judgments effectively [36, 37]. It follows a structured prompting approach and has demonstrated high correlation with both human annotations and system rankings across multiple TREC Deep Learning Tracks (2019–2023). Notably, UMBRELA has been integrated into TREC 2024 RAG for automated evaluation, which further validated its reliability as an alternative to human assessors. We consider UMBRELA a reliable and effective



**Figure 2: Agreement of LLM-based relevance judgments with human annotations across different prompts and relevance judgment tasks.** UMBRELA represents the reproduction of Bing’s LLM assessor introduced in [37]. Otherwise, the top 12 bars ( $H^{-*}$ ) represent human-crafted prompts, while the bottom 12 correspond to LLM-generated prompts. The dashed lines show the mean of agreement in LLM -crafted prompts and human-crafted prompts separately.

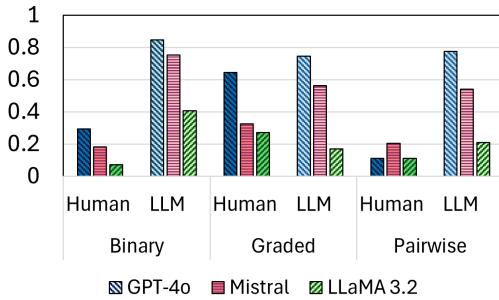
prompt and we believe comparing its performance against human-crafted and LLM-generated prompts in graded relevance judgments would bring interesting insights. Additionally, Table 2 summarizes Figure 2 by providing the mean and variance of agreement scores across the two datasets and different relevance judgments.

We now consider investigating each of our research questions in light of these agreement results.

**RQ1. Impact of Prompts on LLM-based Relevance Judgment Approaches:** Figure 2 and Table 2 reveal significant variance across different LLM-based relevance judgment approaches. Binary and pairwise methods exhibit the least sensitivity to input prompts, maintaining more consistent agreement. In contrast, graded relevance judgments are highly sensitive to prompt variations. We note that while binary and pairwise methods operate with only two choices, graded relevance introduces greater variability. Particularly on graded judgments, GPT-4o demonstrates relatively stable performance but LLaMA 3.2 and Mistral show considerable fluctuations across different prompts.

**RQ2. LLMs as Prompt Generators:** Table 2 shows that LLM-generated prompts generally yield higher average agreement with human annotations. However, for graded relevance judgments, the difference is minimal. This may be due to (i) participants’ greater familiarity with graded assessments or (ii) the inherently subjective nature of assigning relevance levels, which may require more calibration with human annotators. Additionally, LLM-generated prompts exhibit lower variance in agreement compared to human-crafted prompts, indicating less sensitivity to prompt variations.

**RQ3. Prompt Robustness Across LLMs:** Figure 3 analyzes inter-agreement rates among different prompt groups using Krippendorff’s alpha. Here we measure agreement between different prompt’s output, regardless of their alignment with human judgments. The results show that LLM-generated prompts exhibit higher inter-agreement than human-crafted ones, likely due to the greater linguistic diversity in human-generated prompts, as seen in Figure 1. This suggests that LLM-generated prompts are more robust



**Figure 3: Krippendorff’s inter-agreement rate between all the prompts on two datasets.**

than human-crafted ones. While some human-crafted prompts performed well across all models, prompt effectiveness varies significantly between LLMs, with no single prompt consistently excelling across all models. However, for graded assessments, UMBRELA consistently demonstrated high performance across different LLMs and it emerged as one of the most effective prompts across all models. UMBRELA had previously shown strong correlation with human judgments on TREC DL tracks [37]. We hypothesize that UMBRELA’s strong and consistent performance may stem from how its prompt deconstructs the concept of relevance into finer-grained aspects, such as trustworthiness and alignment with intent. This structured approach likely prevents the LLM from relying on its own interpretation of relevance.

**RQ4. Model-Specific Sensitivity to Prompts:** From Figure 2, we observe that GPT-4o demonstrates high consistency across most prompts and all relevance assessment approaches. In contrast, the performance of LLaMA 3.2 and Mistral varies significantly depending on the prompt and assessment method. This variability is further confirmed by the variance of agreement reported in Table 2. Notably, GPT-4o exhibits consistently low variance in agreement, particularly when prompted with LLM-crafted prompts.

## 5 Conclusion and Limitations

In this study, we investigated the sensitivity of LLM-based relevance judgments to different prompting strategies across multiple models. We examined how prompts, whether human- or LLM-generated, influence judgment effectiveness, their robustness across different LLMs, and the extent to which models exhibit variability in response to prompt modifications. One specific outcome is to confirm the performance of UMBRELA as a leading prompt for LLM-based graded relevance assessment. Despite these contributions, our study has limitations. Our human participants primarily had a computer science background with experience writing prompts for LLMs. Additionally, we evaluated only three LLMs as judges, limiting the generalizability of our findings.

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