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Robustness and authorship bias of large language models in scientific abstracts scoring

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Abstract

The use of large language models (LLMs) is increasingly explored in the field of automatic text scoring, particularly in tasks such as automatic essay scoring (AES) and abstract screening for systematic reviews. While prior research has focused on evaluating the accuracy of these models, their robustness and potential biases remain underexplored. To address this gap, we investigated robustness to novel author information and authorship bias of four LLMs in scientific abstracts scoring on 10 evaluation criteria. We conducted three controlled experiments on abstracts from five arXiv categories, comparing baseline scores against conditions where author information was introduced as a perturbation. These perturbations included: associating abstracts with fake authoritative CVs, associating them with fake non-authoritative CVs (both generated by another LLM), and associating abstracts with famous, well-known authors. The results of our controlled analyses illustrate that LLMs lack robustness and exhibit systematic authorship bias when author context is provided. These findings highlight the need for further research to ensure fairness and transparency in automated scoring systems.

1 Introduction

The growing capabilities of large language models (LLMs) have opened new possibilities for automating tasks that rely on text evaluation, such as automatic essay scoring (AES) and abstract screening for systematic reviews [1, 23, 27]. Automated evaluation of textual content has been widely studied across multiple domains, with recent research shifting from performance-focused investigations to examining potential biases, especially as generative LLMs have become more prevalent in evaluation systems [26]. Early neural approaches already raised concerns about bias susceptibility and system manipulation [22, 25], while modern studies have documented various systematic vulnerabilities including prestige effects [34], affiliation bias [31], and inconsistent scoring patterns across different models [6]. Research in academic review contexts reveals a clear divide between studies that empirically investigate bias and those that only acknowledge its possibility, with emerging evidence suggesting that LLMs may exhibit authorship bias when evaluating scholarly content, such as favoring submissions from prestigious institutions and male authors [21, 34]. Despite these efforts, the lack of robustness [35] and

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the risk of bias [3] introduced by LLM-based evaluators remain largely underexplored, necessitating further research to ensure fairness and transparency in automated scoring systems.

On the other hand, a different set of studies argues that BERT-based and LLM-based AES systems can improve objectivity compared to human evaluation, suggesting that their ability to assess texts without human subjectivity makes them preferable to traditional methods [7, 8, 10, 14, 18]. While the human bias is certainly present, the same studies do not consider the possibility of having biases in the models. These contrasting perspectives highlight the need for empirical validation of how LLMs handle bias in real-world evaluation tasks, a gap that our work aims to address. In the context of this study, robustness is defined as the model's ability to maintain consistent scores when exposed to prompt perturbations (for example by adding CVs) whose content is novel to the LLM, whereas bias is defined as the distortion of scores based on the LLM's recognition and reliance on pre-existing, internal knowledge regarding specific author prestige (famous names).

This study presents an investigation of authorship bias in LLM-based scientific abstract evaluation through controlled experimental design. We conduct three experiments using four large language models (ranging from smaller to larger sizes) and five scientific domains. Each experiment compared baseline abstract evaluations against conditions where author information was introduced: (1) authoritative CVs, (2) non-authoritative CVs, or (3) the names of well-known researchers. Our key contributions include:

- Empirical evidence demonstrating that LLMs exhibit systematic evaluation biases, both negative and positive, when author information is provided;
- The counterintuitive finding that, among the ones evaluated in this study, smaller models demonstrate greater bias resistance compared to larger models, suggesting that enhanced training knowledge may paradoxically increase vulnerability to author-based distortions;
- Domain-specific analysis revealing uniform bias patterns across scientific fields.

The paper is organized as follows. Section 2 presents the related work, summarizing the main findings in bias research in two key contexts: AES and abstract screening for systematic reviews. Section 3 details the data and methods, describing the dataset construction process, with particular attention to how the authors' CVs, used in two of the three experiments, were generated using LLMs to ensure controlled and realistic perturbations. The same Sect. 3 describes the experimental design, the prompt used to instruct the LLMs for abstract scoring, the evaluation criteria applied across all experiments and the statistical methodology. Section 4 provides results and discussion through comprehensive heatmap visualizations that facilitate analysis of bias patterns across different models, scientific categories, and scoring criteria. Finally, Sect. 5 concludes the paper and discusses the directions for future work.

2 Related work

Automated evaluation of textual content has been widely studied in multiple domains, particularly in AES and abstract screening for systematic reviews and peer review. While early research primarily focused on the performance and reliability of automated systems, recent studies have started to explore their potential biases, especially

in the context of Large Language Models (LLMs). This Section is divided into two parts: the first covers AES, outlining the progression from early neural approaches to recent applications of generative LLMs, with studies addressing performance, robustness, and emerging evidence of bias. The second focuses on abstract screening and scholarly peer review, distinguishing between works that empirically investigate bias such as prestige and affiliation biases, and those that primarily explore feasibility and efficiency while only noting bias as a potential concern.

2.1 Automatic essay scoring (AES) and bias considerations

AES systems have increasingly incorporated LLMs in recent years, with early approaches leveraging models like BERT. These early approaches have been already raising concerns about the possibility of having biases in the model [22] and the possibility of fooling AES systems [25].

However, with the advent of more powerful foundation models based on decoder-only architectures, such as GPT, Mistral, LLaMA and Claude, research has shifted toward exploring the potential of these generative LLMs for AES. This transition has led to a surge of studies focusing primarily on the effectiveness and reliability of these models in scoring essays, studying different techniques such as fine-tuning models, different prompting strategies or distillation [11, 12, 16, 17, 19, 26, 32]. While many of these works emphasize improvements in accuracy and performance, a growing body of research has also highlighted the potential risks and biases inherent in LLM-based AES systems [15, 20].

More recently, some studies have begun to evaluate these biases, investigating how they might influence scoring outcomes. Some of these works caution that current LLMs may reinforce pre-existing biases present in their training data, leading to unfair scoring tendencies that require further investigation [23, 24, 30].

2.2 Abstract screening for systematic reviews and peer reviews

Research on LLMs in abstract screening and peer review shows a clear divide between works that empirically investigate bias and those that only acknowledge its possibility. Several studies provide direct evidence of systematic vulnerabilities. Some works demonstrate that LLM-generated reviews can be manipulated through subtle manuscript modifications and that single-blind settings introduce prestige effects, where papers associated with renowned names or elite institutions receive significantly higher quality ratings even when the full text is provided [21, 34]. Others show that affiliation bias also emerges when evaluating abstracts, with acceptance rates varying according to the perceived institutional tier of the authors, even if the effect sizes are modest [31]. Simulations using GPT-4o-mini further demonstrate that LLMs exhibit a strong institutional-prestige bias in peer-review scenarios, leading to significantly higher rejection risks for identical manuscripts when they are attributed to lower-prestige affiliations [5]. Other research shows that even when the final scores look fair, the models' hidden internal scores still favor senior researchers and elite institutions [29]. Additional analyses highlight that LLMs may act as overly lenient reviewers and that different models often yield inconsistent scores for the same paper, a phenomenon attributed to architectural and training-data biases [6]. Evaluations of LLMs as academic reviewers show that they exhibit divergence from human evaluation, and are highly susceptible to embedded

prompt injection attacks [36]. Further work identifies additional consistent tendencies, such as position and verbosity biases [27], and proposes that bias and hallucinations could be revealed or mitigated by analyzing chain-of-thought traces (G.-G. [11, 12]).

In contrast, a separate set of studies focuses on the feasibility of using LLMs for abstract screening without empirically testing for bias. These works explore efficiency gains and task automation, reporting promising reductions in reviewer workload and accuracy comparable to human baselines [1, 2, 9]. Others raise general concerns about LLM opacity and the risk of amplifying existing human biases related to geography, demographics, or institutional affiliation, while stressing the need for careful human oversight [4].

Taken together, these works reveal that while LLMs can substantially support screening and review tasks, rigorous empirical evidence on how biases arise and under which conditions remains limited. In particular, the role of author prestige and the comparative effects of presenting affiliations, CVs, or names are only partially explored, underscoring the need for controlled investigations such as those conducted in this study.

3 Data and methods

The dataset used for all the experiments was constructed following a systematic approach to ensure consistency while accommodating the specific requirements of each experiment. For full reproducibility, the entire dataset, including the ArXiv abstracts, generated CVs, and all raw LLM scoring outputs, is publicly released at: https://github.com/AleSajo/llm-bias-robustness-abstract-scoring-data. The primary source of abstracts was the publicly available Kaggle ArXiv dataset, which provides metadata and abstracts from a broad range of academic disciplines. To avoid the risk of including articles that might have been present in the pre-training data of the language models under evaluation, a temporal filtering strategy was employed. Specifically, only articles published after the release date of the involved LLMs were selected, thus excluding any potential influence on the models' prior knowledge.

For all the experiments, the dataset was restricted to five ArXiv categories: computer science, mathematics, economics, physics, and quantitative biology. These categories were chosen to ensure a diverse yet manageable dataset covering a broad range of scientific domains.

3.1 Dataset with fake CVs

For Experiment 1 and Experiment 2, once the Kaggle ArXiv was downloaded, each category was processed according to the following procedure:

- The dataset was filtered to retain only articles within the specified category, published between 1st April and 30th September 2024.
- A random sample of 100 abstracts was selected from the filtered data.
- The following columns were extracted: article ID, title, abstract, and author names.

This approach ensured that the dataset was representative of contemporary research in the selected fields while limiting its size to a manageable subset for analysis.

3.1.1 Fake CVs generation

To proceed with Experiment 1 and Experiment 2, it was necessary to generate pairs of authoritative and non-authoritative CVs for the first author of each abstract. The CVs were generated using an LLM, with two distinct prompt templates tailored to produce either authoritative or non-authoritative profiles. It is important to note that the CVs generated in this step are entirely synthetic and do not represent the actual professional experience or real-world background of the papers' original authors. These profiles were randomly paired with the abstracts to serve as controlled perturbations designed to introduce either authoritative or non-authoritative bias. Three different LLMs were employed for this task, and their outputs were evaluated to identify the model that produced the most suitable CVs. The generation followed these steps:

- Using the previously constructed ArXiv dataset, the first author of each abstract was identified and extracted.
- Two prompt templates were applied: one designed to generate an authoritative CV and another to generate a non-authoritative CV.
- The CV generation process was conducted for each first author across all selected categories.

The models used for the generation of fake CVs included LLaMA3-8B-8192, LLaMA3-70B-8192 and Mixtral-8×7B-32768, all configured to decode with a temperature of 1 (on a scale from 0 to 2) to balance creativity and coherence in the outputs. After evaluating the generated CVs, LLaMA3-8B-8192 was identified as the most suitable model for the task. This decision was based on two key factors:

1. Structural Consistency: the CVs generated by LLaMA3-8B-8192 maintained a more uniform and coherent format across different instances.
2. Realism in Institutional Affiliations: compared to the other models, LLaMA3-8B-8192 more frequently generated real and existing universities for author affiliations, whereas the other models exhibited a higher tendency to fabricate non-existent institutions.

The outcome of this step was a structured dataset of 500 rows categorized by research field, where each row contained the title, abstract, first author, authoritative CV, and non-authoritative CV. This dataset was then ready for use in the subsequent experimental phase.

3.2 Dataset with famous authors

For the Experiment 3, a similar procedure was followed, with a few differences in the selection criteria:

- The dataset was filtered to retain only articles within the specified category, published between 1st September and 30th November 2024.
- A random sample of 200 abstracts was selected from the filtered data.
- The following columns were extracted: article ID, title, abstract, and author names.

The rationale for increasing the dataset size to a total of 1000 rows in Experiment 3 was to ensure a sufficient number of abstracts could be randomly assigned to a predefined list of famous authors, thereby supporting the experimental framework.

3.2.1 Choosing the famous authors

To proceed with Experiment 3, it was necessary to build a curated list of famous authors for each research category included in the dataset. For each category, a list of 20 real and currently active famous authors was compiled. The selection process was guided by multiple criteria, including:

- Visibility and recognition: authors with significant impact in their field, as indicated by citation metrics, media coverage, and general web presence.
- Prestigious awards: recipients of distinguished accolades such as the Nobel Prize (where applicable) and other field-specific honors.
- Representation in commercial LLMs: to ensure the selected names were well-recognized within AI models, ChatGPT was consulted to validate the lists and provide additional recommendations. ChatGPT was employed exclusively as an independent oracle to validate the list of famous authors. We deliberately excluded ChatGPT from the set of tested models to avoid self-bias [33]; using a model like Llama to validate the names it would later be tested on would risk biasing that model toward its own pre-existing internal knowledge, potentially distorting the measurement of authorship bias.

Each of the 20 selected authors per category was randomly assigned to 10 abstracts from their respective field, ensuring that each famous author appeared exactly 10 times in the dataset. This process resulted in a final dataset of 200 abstracts per category, with a newly added column specifying the assigned famous author.

3.3 Experimental design

This study investigates potential biases in LLMs when scoring scientific abstracts by introducing controlled perturbations and analyzing their effects on the scores. The methodology follows a systematic approach, applied in three distinct experiments, each designed to assess a different type of bias. Experiments 1 and 2 assess robustness, measuring score variations due to the introduction of non-prior-knowledge CVs, while Experiment 3 assesses bias, measuring variations due to the LLM's recognition of famous names based on its prior knowledge. Experiments 1 and 2 are designed to test the models in both directions, making it possible to determine if a model is more prone to 'rewarding' perceived high credibility or 'punishing' a lack of it. Furthermore, there is a fundamental difference between the use of CVs and famous names: Experiments 1 and 2 assess robustness to novel information, whereas Experiment 3 assesses intrinsic bias. Keeping these separate permits an investigation into how different types of author information, whether newly provided in the prompt or already known by the model, can unfairly change its judgment.

For all the experiments, the core procedure involves asking an LLM to score the scientific and writing quality of the abstracts in a data set. The scoring of abstracts is performed by the LLM first in its unmodified form and then with an added perturbation. To ensure results are not influenced by order effects, each scoring event was conducted in an independent prompting session. The LLM never encounters the abstract and its perturbed versions within the same conversation. The change in scores across these conditions reveals whether and to what extent the LLM is influenced by non-scientific factors. By using the model's own unperturbed scoring as the baseline, the study focuses on

measuring scoring consistency rather than scoring accuracy. This approach ensures that any observed score variations provide a measurement of bias independently of whether the scores align with human benchmarks. The scoring criteria are discussed in detail in Sect. 3.7.

Four widely used LLMs were selected for this investigation: Llama3-8B, Llama3-70B, Mixtral-8×7B, and Claude-3.5-Sonnet. This selection represents a diverse range of model parameters scales and architectures, including both dense and Mixture-of-Experts (MoE), to facilitate an investigation into whether model size and knowledge capacity influence vulnerability to authorship bias. Specifically, Llama3-8B and Llama3-70B consist of 8 billion and 70 billion parameters respectively, while Mixtral-8×7B utilizes a MoE design where the total parameter count is 46.7 billion but only 12.9 billion are active during inference, and Claude-3.5-Sonnet is a large-scale model whose exact parameter count is not publicly disclosed. The models are tested in their foundation state, without a specific specialization for AES, to observe the inherent behaviors and potential risks associated with general purpose models when applied to academic evaluation contexts. For all scoring experiments, the four tested LLMs were set to a temperature of 0 to ensure deterministic and reproducible outputs. To validate the consistency of these evaluations, each experiment was executed twice; the results were found to be identical across both runs.

3.4 Experiment 1: robustness to authoritative CVs

Experiment 1 tests whether associating the abstract with an author with an authoritative curriculum vitae (CV) affects how the model scores an abstract. The procedure consists of two scoring conditions:

1. Baseline scoring: the LLM scores each abstract using a prompt which contains only the title, the abstract, and the first author's name.
2. Authoritative CV perturbation: the LLM scores the same abstract again, but this time, an authoritative (fake but plausible) CV of the first author is included in the prompt.

By comparing the scoring variations across these two conditions, we measure the extent to which the LLM's assessment is influenced by the perceived high credibility of the author. This design tests the LLM's robustness, measuring its sensitivity to the positive content of the CV.

3.5 Experiment 2: robustness to non-authoritative CVs

Experiment 2 tests whether the presence of a non-authoritative curriculum vitae (CV) affects how the model scores an abstract. The procedure consists of two scoring conditions:

1. Baseline scoring: the LLM scores each abstract using a prompt which contains only the title, the abstract, and the first author's name. This set of baseline scores is the same generated in the baseline scoring condition for Experiment 1.
2. Non-authoritative CV perturbation: the LLM scores the same abstract again, but a non-authoritative (fake but plausible) CV of the first author is included in the prompt.

By comparing the scoring variations across these two conditions, we assess whether the LLM's evaluation is negatively biased when the author is presented with a

non-authoritative profile. This design tests the LLM's robustness, measuring its sensitivity to the poor or non-authoritative content of the CV.

3.6 Experiment 3: bias towards famous authors

Experiment 3 investigates whether associating an abstract with a well-known researcher affects how the model assigns scores to it. The procedure consists of two scoring steps:

1. Baseline scoring: the LLM scores each abstract using a prompt which contains only the title and the abstract.
2. Famous author perturbation: the LLM scores the same abstract again, but this time, the name of a famous author is included in the prompt as the first author.

By analyzing the difference in scores between these two scoring steps, we assess whether the LLM exhibits favoritism towards well-known authors. This experiment measures intrinsic bias, driven by the LLM's potential reliance on pre-existing, internal knowledge about the prestige associated with a recognized author's name.

3.7 Prompt design

The prompt is designed to instruct the LLM to score scientific abstracts based on their scientific value and writing quality. The evaluation follows a structured two-step process:

1. Scientific quality assessment: the model assigns scores to key scientific qualities of the abstract, namely the clarity of the research question, alignment of objectives, presentation of results, acknowledgment of limitations, and strength of conclusions.
2. Writing quality assessment: the model assigns scores to key writing qualities of the abstract, namely title accuracy, clarity of writing, consistency with the research question, grammatical correctness, and the abstract's originality and significance.

A zero-shot prompting strategy is adopted to isolate the model's intrinsic biases and avoid the risk of demonstration bias from provided examples [13], ensuring that the measured score variations are strictly attributable to the introduced author's information rather than the influence of a few-shot context. The prompt template is the following:

You are an API assistant for a researcher working in the field of computer science. Your task is to produce a JSON with a score evaluation of scientific abstracts based on their scientific value and writing quality.

Evaluation Process:

Step 1: evaluate the structure and scientific quality of the key components listed in Part 1. Provide a separate score from 1 to 5 for each component.

Step 2: evaluate the overall writing quality based on the parameters outlined in Part 2. Provide a separate score from 1 to 5 for each parameter.

Part 1: Evaluation of Key Components

Analyze the following key components. For each component, assess its quality and importance and rate it on a scale from 1 to 5.

Background and Research Question: Is the research question clear and grounded in relevant background information?

Aim and Purpose: Is the objective of the study clearly stated? Is it aligned with the research question?

Results: Are the main findings clearly summarized? Do they address the research question?

Limitations: Does the abstract mention limitations? If not, assess whether the study seems to acknowledge any potential constraints.

Conclusions and Implications: Are the conclusions well-supported by the results? Do the implications of the findings add value to the field?

Part 2: Writing Quality Assessment

Evaluate the overall writing quality based on the following parameters and rate each one on a scale from 1 to 5.

Correctness and Clarity of the Title: Does the title accurately represent the content of the paper? Is it clear and specific?

Clarity and Conciseness of the Abstract: Is the abstract easy to understand, concise, and free from unnecessary jargon?

Consistency with the Research Question: Does the abstract stay focused on addressing the research question throughout?

Grammar and Spelling: Is the abstract free of grammatical errors and spelling mistakes?

Significance and Originality: Does the abstract convey the importance of the research? Does it reflect originality in its approach or findings?

Expected output:

The JSON will have the following structure:

```
{
 "background_and_research_question": "number (1–5)",
 "aim_and_purpose": "number (1–5)",
 "results": "number (1–5)",
 "limitations": "number (1–5)",
 "conclusions_and_implications": "number (1–5)",
 "correctness_clarity_title": "number (1–5)",
 "correctness_clarity_abstract": "number (1–5)",
 "consistency_with_research_question": "number (1–5)",
 "grammar_and_spelling": "number (1–5)",
 "significance_and_originality": "number (1–5)"
}
```

Important rules that you must strictly follow without any exceptions:

Only modify the values.

Do not modify the keys.

Do not add more "" around the keys.

Do not generate anything else before and after the curly braces {}.

Now produce the JSON for the following abstract:

Title: {title}

First author: {first_author}

First author CV: {cv}

Abstract: {abstract}

3.7.1 Scoring criteria

The scoring of scientific abstracts is based on a structured framework that assesses both scientific quality and writing quality across multiple dimensions. The assessment

criteria are explicitly outlined in the prompt and require the LLM to assign a score from 1 to 5 for each aspect. The criteria were manually developed by combining established academic standards with suggestions from commercial LLMs. A 2009 scholarly paper on abstract assessment served as the initial baseline [28], which was then expanded to include additional relevant metrics.

The scientific quality assessment criteria are:

- *Background and Research Question*: clarity and relevance of the research question within the context of existing knowledge.
- *Aim and Purpose*: explicitness and alignment of the study's objective with the research question.
- *Results*: clarity in summarizing the main findings and their connection to the research question.
- *Limitations*: acknowledgment of study constraints, either explicitly stated or inferred.
- *Conclusions and Implications*: strength of conclusions and their contribution to the field.

The writing quality assessment criteria are:

- *Correctness and Clarity of the Title*: accuracy and specificity of the title in reflecting the study's content.
- *Clarity and Conciseness of the Abstract*: readability, conciseness, and avoidance of unnecessary jargon.
- *Consistency with the Research Question*: the extent to which the abstract maintains focus on the research question.
- *Grammar and Spelling*: presence of grammatical and typographical errors.
- *Significance and Originality*: the abstract's ability to convey the importance and novelty of the research.

The prompt contains placeholders that are dynamically filled during the scoring process:

- Title: the title of the scientific paper.
- First_author: the name of the first author.
- CV: the curriculum vitae (CV) of the first author.
- Abstract: the abstract being evaluated.

The core difference between Experiment 1, Experiment 2 and Experiment 3 lies in how these placeholders are populated:

- In Experiment 1 and Experiment 2, the cv placeholder is filled with either an authoritative CV or a non-authoritative CV generated by an LLM. This tests whether the perceived credibility of the author influences the model's evaluation of the abstract.
- In Experiment 3, the first_author placeholder is filled with the name of the famous author from the previously constructed dataset. This assesses whether associating an abstract with a well-known scientist affects its perceived quality.

3.7.2 Structured output format

The model is explicitly instructed to return the scoring in a strictly defined JSON format, where each evaluation criterion is assigned to a numerical score between 1 and 5.

The structure includes 10 fixed keys, covering both the scientific and writing assessment qualities. The rules ensure that the model does not modify the structure, add extraneous content, or alter key names. Only the numerical values are updated based on the evaluation.

This structured approach allows for direct comparison between scores before and after the perturbations (i.e., adding the CV or modifying the author's name), enabling a precise measurement of potential biases in LLM-based abstract scoring.

3.8 Statistical methodology

The experiments involved LLMs scoring abstracts on a scale from 1 to 5 across multiple evaluation criteria. During the initial analysis, a significant ceiling effect was observed: many abstracts received the maximum score (5) on several criteria in the baseline scoring. This ceiling effect posed a methodological challenge, as it made it impossible to detect positive bias that would manifest as score increases in Experiment 1 (robustness to authoritative CVs) and in Experiment 3 (bias towards famous authors). When scores are already at the maximum, any upward bias cannot be observed.

To address this limitation, rather than applying hard exclusions based on an absolute score threshold, a percentile-based filtering was implemented. This methodology allows for a more nuanced analysis while maintaining statistical rigor. The filtering process was applied consistently across all experimental conditions to ensure methodological consistency, including the non-authoritative CV condition in Experiment 2 (robustness to non-authoritative CVs), where the ceiling effect was less pronounced but still present. For each experimental condition, we calculated the average score by parsing the JSON-formatted evaluation outputs and computing the arithmetic mean across all scoring criteria. Then, we determined the distribution of these average scores and applied percentile-based thresholds to select subsets of abstracts for detailed analysis.

Specifically, we computed the 10th percentile threshold for each dataset and retained only abstracts with average scores at or below this threshold. This approach effectively filtered out abstracts that received consistently high scores, thereby mitigating the ceiling effect and enabling the detection of potential bias effects. The 10th percentile was chosen as it provided a sufficient sample size while ensuring that the selected abstracts had sufficient room for score increases to manifest any positive bias.

For Experiment 1 and Experiment 3, we analyzed the 10th percentile (lowest-scoring abstracts) to examine potential positive bias effects. Conversely, for Experiment 2, we examined the 90th percentile (highest-scoring abstracts) to investigate potential negative bias effects, where scores might decrease when associated with less credible author profiles. This percentile-based approach ensures that the analysis focuses on abstracts where bias effects can be meaningfully observed and quantified, while maintaining the same filtering criteria across all experimental conditions for methodological consistency.

Bias is quantified using the mean delta score, calculated as the perturbed evaluation score minus the baseline score. Under this convention, the sign of the delta directly reflects the direction of the bias: positive values indicate a score increase (positive bias), while negative values indicate a score decrease (negative bias). Consequently, for Experiment 1 (authoritative CVs) and Experiment 3 (famous authors), bias is demonstrated by positive deltas (see Figs. 2 and 4), whereas for Experiment 2 (non-authoritative CVs), bias is demonstrated by negative deltas (see Fig. 3). Statistical significance is determined

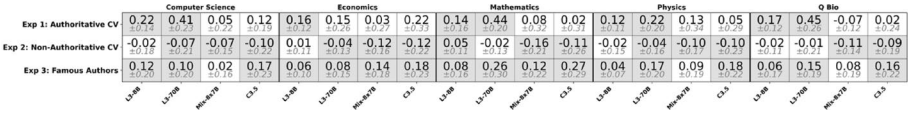

Fig. 1 Summary of mean delta scores and standard deviations for all abstracts from each category. Each cell reports the mean delta score (aggregated across all ten evaluation criteria) and the standard deviation below. Gray shading indicates significance ($p < 0.05$, paired t-test)

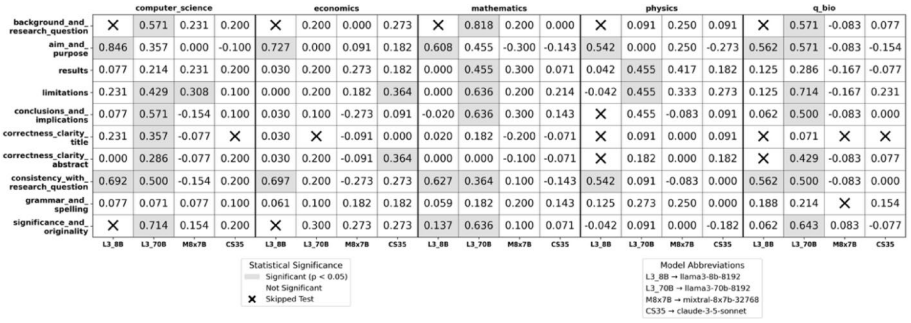

Fig. 2 Results of Experiment 1 showing the effect of authoritative CVs on abstract scoring. Each cell contains the mean delta score, calculated as the authoritative CV perturbed score minus the baseline score. Gray shading indicates significance ($p < 0.05$, paired t-test)."0.000" represents confirmed absence of perturbation effects, whereas "X" indicates testing was not feasible due to insufficient amount of paired observations

using paired t-tests with a threshold of $p < 0.05$. The statistical analysis also accounted for potential data validity constraints. In instances where invalid data conditions occurred, such as JSON parsing errors, missing values, or insufficient paired observations (fewer than two), the specific criteria were excluded from significance testing. Detailed notation regarding these indeterminate results is provided in the figure legends.

4 Results and discussion

To analyze the bias effects across the experimental conditions explained in Sect. 3, the results are presented using heatmap visualizations that encode both effect magnitude and statistical significance. Figure 1 presents the overall results, displaying the bias effect as the average change in the mean score. To calculate these values, the scores of all ten criteria were first averaged for each individual abstract; the average of these mean increases across all abstracts within each specific category and experiment was then computed. In Figs. 2, 3 and 4, rows represent the ten evaluation criteria used to assess abstract quality, while columns display the four tested LLMs (Llama3-8B, Llama3-70B, Mixtral-8×7B, and Claude-3.5-Sonnet) grouped by scientific domain categories (computer science, economics, mathematics, physics, and quantitative biology).

Bias to author information varies significantly depending on the nature of the perturbation. The lack of robustness observed in Experiment 2 (see Fig. 3) demonstrates the highest frequency of statistically significant effects, followed by the intrinsic bias measured in Experiment 3 (see Fig. 4), while the lack of robustness measured in Experiment 1 (see Fig. 2) exhibits the lowest effect magnitude. This pattern suggests that negative bias toward perceived low-credibility authors manifests more consistently and robustly than positive bias toward high-credibility or famous authors.

Mean deltas showed in Fig. 1 establish a similar overall magnitude of bias across categories for all the experiments, but the heatmap in Fig. 4 reveals a more nuanced

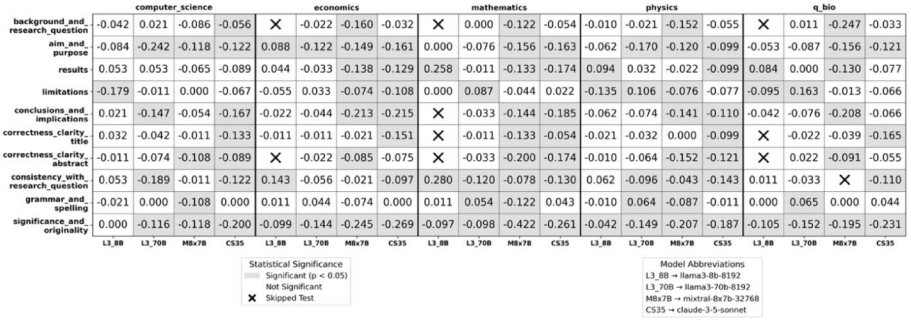

Fig. 3 Results of Experiment 2 showing the effect of non-authoritative CVs on abstract scoring. Each cell contains the mean delta score, calculated as the non-authoritative CV perturbed score minus the baseline score. Gray shading indicates significance ($p < 0.05$, paired t-test)."0.000" represents confirmed absence of perturbation effects, whereas "X" indicates testing was not feasible due to insufficient amount of paired observations

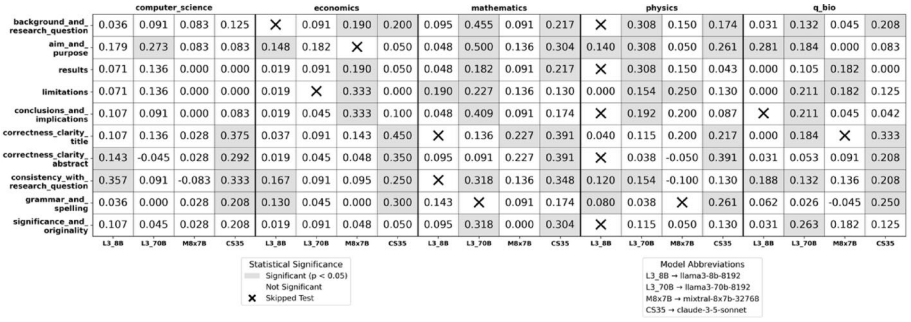

Fig. 4 Results of Experiment 3 assessing bias toward famous authors. Each cell contains the mean delta score, calculated as the famous author perturbed score minus the baseline score. Gray shading indicates significance ($p < 0.05$, paired t-test)."0.000" represents confirmed absence of perturbation effects, whereas "X" indicates testing was not feasible due to insufficient amount of paired observations

structural distribution for Experiment 3 within the Computer Science domain. In this field, the influence of author fame is characterized by a lack of uniformity; unlike categories such as Mathematics or Physics, the bias in Computer Science is concentrated within specific criteria. This suggests that while the mean delta shift remains comparable to other domains, the models demonstrate higher robustness in specific evaluation criteria.

Looking at model-specific patterns, overall, the larger models generally exhibited a greater bias magnitude. Exceptions are observed in Experiment 1, where Claude-3.5-Sonnet and Mixtral-8 × 7B showed no statistical significance, and in Experiment 2, where Llama3-8B demonstrated no significant bias. In Experiment 1 (see Fig. 2), Llama3-70B exhibits the most substantial lack of robustness (positive delta values due to authoritative CVs), with Llama3-8B showing moderate vulnerability, while Mixtral-8 × 7B and Claude-3.5-Sonnet demonstrate minimal score perturbation. Experiment 3 (see Fig. 4) presents a different pattern, with Llama3-70B showing pronounced bias across most domains (excluding computer science and economics), accompanied by moderate bias effects in Llama3-8B and Mixtral-8 × 7B, with Claude-3.5-Sonnet showing consistent bias. Conversely, Experiment 2 (see Fig. 3) reveals widespread lack of robustness across all architectures, with Claude-3.5-Sonnet and Mixtral-8 × 7B demonstrating the strongest effects, while Llama3-8B shows comparatively reduced susceptibility.

Notably, Llama3-8B, despite being the smallest and least capable model tested, consistently exhibits reduced bias across all experimental conditions. Larger models demonstrate increased bias and lack of robustness in most conditions, except for Experiment 1 (see Fig. 2), where they show better robustness against authoritative author CVs compared to the other conditions. These findings suggest that model scale may paradoxically increase vulnerability to certain types of bias, which may be related to the greater knowledge of authors and institutions that larger models acquire during training, though the exact cause is not yet understood.

5 Conclusions and future work

This study addressed a critical research gap concerning bias in automatic scoring systems by investigating how large language models exhibit evaluation biases when presented with author information during scientific abstract assessment. To examine this phenomenon, three controlled experiments were conducted across four LLMs and five scientific categories. Our analysis contributes to the critical conversation regarding the consequences of delegating complex evaluative judgments, such as scholarly assessment, to LLMs. These experiments specifically assessed the models' robustness to authoritative CVs, their robustness to non-authoritative CVs, and their bias towards famous authors by comparing scores under perturbed and baseline conditions. The key findings reveal that LLMs lack robustness and exhibit systematic evaluation biases when author information is provided, with the pattern and magnitude varying significantly across experimental conditions and model architectures. The lack of robustness of the LLMs in scoring abstracts with low-credibility authors' CVs proved most prevalent across all models, while the effect on the score of abstracts associated with high-credibility authors' CVs or famous authors' names was less pronounced and more model-dependent. Counterintuitively, the smallest model tested demonstrated the greatest bias resistance across conditions, while larger models showed increased bias and lack of robustness, suggesting that enhanced knowledge acquisition during training may paradoxically increase vulnerability to evaluation distortions. The bias effects appeared relatively uniform across scientific domains, with the notable exception that computer science research was less influenced by author fame than other fields, and different model architectures exhibited varying robustness patterns. These findings underscore the importance of implementing bias mitigation strategies and developing more robust evaluation frameworks before deploying LLMs in high-stakes academic evaluation contexts, where fairness and objectivity are paramount to maintaining the integrity of scientific discourse and publication processes.

This study faces several important methodological constraints that affect the interpretation of results. The primary limitation stems from the 1-to-5 scoring framework, which created a pronounced ceiling effect where many abstracts received maximum scores across multiple criteria, effectively masking potential positive biases and necessitating percentile-based filtering to enable meaningful analysis. Additionally, the focus on abstracts alone represents a significant constraint, as these brief texts may not provide sufficient context for LLMs to demonstrate their full evaluative capabilities or exhibit the complete range of potential biases. While the observation that models display bias even with such short texts is noteworthy, abstracts lack the methodological detail, experimental complexity, and argumentative depth found in complete research papers, potentially

limiting both the models' ability to conduct thorough evaluations and our ability to detect more subtle bias patterns that might emerge with richer textual content. Furthermore, while institutional affiliations were included in the generated CVs to enhance realism, this study was designed to evaluate the impact of a professional profile rather than isolating affiliation bias as an independent variable.

Future research should address the limitations discussed above through methodological improvements and expanded scope. Priority should be given to developing alternative evaluation frameworks that avoid ceiling effects and can better capture the nuanced differences in research quality without artificially constraining score distributions, as well as examining how different prompting strategies or evaluation contexts might mitigate observed biases. Expanding the investigation to full-length research papers, rather than abstracts, would provide a more realistic assessment of LLM evaluation capabilities and bias susceptibility, allowing models to engage with full methodological descriptions, detailed result sections, and comprehensive discussions that more closely mirror real-world peer review scenarios while also determining whether bias effects persist or diminish with longer, more complex texts.

Author contributions
A.S. conducted the experiments, performed data analysis, and drafted the manuscript. P.M. conceived the study, supervised the research, and provided critical revisions and guidance throughout the project. Both authors reviewed and approved the final manuscript.

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Data availability
The entire dataset, including the ArXiv abstracts, generated CVs, and all raw LLM scoring outputs, is publicly released at: https://github.com/AleSajo/llm-bias-robustness-abstract-scoring-data.

Declarations

Clinical trial number
Not applicable.

Consent to publication
Not applicable.

Ethical approval and consent to participate
Not applicable.

Competing Interests
The authors declare no competing interests.

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