Journal of Technology Informatics and Engineering (JTIE)
Vol. 5 No. 1 April 2026
E-ISSN: 2961-9068; P-ISSN: 2961-8215, Pages 271-287
DOI: https://doi.org/10.51903/jtie.v5i1.476

Bias and Hallucination Evaluation in LLMs

Sathiyaseelan R.*[1], Ganga P.[2], Reshma A. B.[3]
Email: rs_shakthi@yahoo.co.in, ashokganga88@gmail.com, reshmaab2004@gmail.com
Orcid: https://orcid.org/0009-0001-4718-5693, https://orcid.org/0009-0009-5247-9598, https://orcid.org/0009-0001-5585-3380
[1,2,3]*Department Faculty of Computer Science and Engineering, Arunai Engineering College, Tiruvannamalai, India, 606603*
*Corresponding Author

Abstract
The largest failure modes of LLMs to-date, bias and hallucination, have measurable harms in contexts where factuality and fairness are paramount. Both areas have experienced significant research growth; however, prior work on each generally operates as a disparate body of research, and there is a gap in a methodological framework for jointly measuring, tracing, and reducing both under the same experimental conditions. We provide that framework through an empirical evaluation (not a survey) of bias propagation and hallucination generation on four illustrative domains (medical, legal, finance, human resources) through a framework that addresses the three research questions: how can bias and hallucination be measured simultaneously through a replicable, domain-specific protocol; which techniques yield statistically meaningful improvements and a consistency of effectiveness; and how do causally informed methods fare against retrieval methods when tested for factual error reduction. We report new experiments using the GPT-4, LLaMA-2, and Falcon-7B models on the MIMIC-III, CrowS-Pairs, Yahoo Finance Q3 and XNLI-HR benchmarks while keeping our prompts uniform and our random seeds fixed. Methods included structural causal modeling, retrieval-augmented generation, uncertainty-aware RLHF, and hallucination-specific fine-tuning, with experiments on each method separately before merging them into combined frameworks. We observe that RAG achieved a 45% reduction in hallucination rates and that our causally guided active learning method reduced bias disparity by 25%; together, they substantially outperform either method alone. This contributes to a repeatable method for auditing bias and hallucinations, helping ensure alignment with EU AI Act standards and similar requirements.

Keywords: *AI Bias Detection, Causal Inference Modeling, Hallucination Mitigation Strategies, Large Language Model Evaluation, Retrieval-Augmented Generation.*

I. INTRODUCTION

Automated language systems have dramatically transformed over the last decade; shifting from limited rule-based pipelines to large-scale neural systems capable of open-ended generation, reasoning, and contextual dialogue (Asso et al., 2025; Luo, 2025; Melyani et al., 2024). This evolution has produced surprising utility across contexts, from clinical decision support to drafting legal documents, and, in doing so, has surfaced a new category of failure that performance-oriented benchmarks typically fail to identify. Perhaps most notable and consequential among these failures are bias (a systematic skewing of outputs toward socially constructed stereotypes implicit in training corpora) and hallucination (the confident assertion of facts for which there is no empirical grounding). These failure modes are not incidental bugs but systemic artifacts arising from the fundamental way current LLMs are trained on vast, diverse, web-sourced datasets that reflect the very inequalities and factual errors from which they were born (Bender et al., 2021; Weidinger et al., 2021). In high-stakes deployment settings, the

Received on December, 2026; Revised on January, 2026; Accepted on February, 2026; Published on April, 2026

downstream impacts of these failures rise above mere user frustration and into domains of institutional liability, patient safety, and legal consequences.

Existing research has tackled these failure modes from several angles. Studies on the impact of training data have demonstrated that skew in pre-training datasets directly exacerbates disparities along demographic lines in model outputs (Caliskan et al., 2021; Dhamala et al., 2021). Concurrently, work on factual consistency has argued that the probabilistic token prediction at the heart of autoregressive generation intrinsically pits fluency against factual accuracy – a tension which retrieval-augmented generation attempts to resolve by grounding models in real-world knowledge (Lewis et al., 2020). Approaches to aligning model behavior with human values via reinforcement learning from human feedback have shown the ability to improve instruction-following and output safety, but have struggled to address deep-seated biases across disparate contexts (Ouyang et al., 2022). Most recently, structural causal modeling has provided a principled counterpoint to purely statistical debiasing methods, positing a framework for understanding bias not just by observing its manifestations but by tracing it to its underlying causes (Pearl & Mackenzie, 2018). What is missing, however, is a comprehensive empirical framework that can jointly quantify bias and hallucination across real-world deployment contexts using consistent, reproducible experimental settings.

The implications of this gap are methodological and practical: Methodologically, these failure modes are typically considered separately in existing evaluations, failing to account for how they can coexist and interact. In practice, while fields with high-stakes deployments, such as medicine, law, finance, and human resources, carry the greatest risks, each has received only piecemeal attention, using incomparable methods and benchmarks. The lack of a standardized, cross-domain evaluation framework with comparable prompts, settings, and metrics means practitioners cannot compare mitigation strategies and that it is nearly impossible to generalize results from one sector to another. The situation is exacerbated by the rapid deployment of LLMs, which far outpace the development of governance mechanisms for auditing LLM behavior at scale (Bommasani et al., 2022; Liang et al., 2022).

This study addresses this gap with a structured empirical examination of bias and hallucination across four representative deployment domains: healthcare, law, finance, and human resources. Three research questions guide our analysis: how can bias and hallucination be simultaneously measured with reproducible, domain-specific benchmarks; which mitigation strategies, including retrieval augmentation, causal intervention, fine-tuning and human feedback, demonstrably and consistently improve performance on these dimensions; and, how well does causal modeling perform against retrieval methods on reducing both factual error and demographic skew? We

conducted original experiments using GPT-4, LLaMA-2, and Falcon-7B on the benchmarks MIMIC-III, CrowS-Pairs, Yahoo Finance Q3, and XNLI-HR, with controlled prompts and fixed random seeds to ensure comparability of results.

We make three key contributions. First, we present a repeatable cross-domain evaluation protocol to compare bias and hallucination across models and deployment domains. Second, we provide empirical results showing that an integrated approach, incorporating retrieval-augmented generation and causal-guided active learning, surpasses single-method approaches by reducing hallucination rates by up to 45% and bias disparities by 25% across evaluated domains. Third, we offer a system architecture reference for bias and hallucination auditing that practitioners can use to align with regulations such as the EU AI Act. Collectively, these contributions move towards the goal of building LLM systems that are not just capable, but verifiably fair, factually sound, and institutionally accountable.

II. LITERATURE REVIEW

Work on bias in large language models originated in seminal studies showing that word embeddings trained on web-scale corpora readily absorb and reproduce societal stereotypes due to statistical co-occurrence (Caliskan et al., 2021). An initial insight from embedding geometry morphed into an argument about generative models in which biased associations no longer emerge as latent vectors but as an observable gap between different demographic groups that are described or neglected. Dhamala et al. (2021) gave an operational definition to this argument in their BOLD benchmark, the first large-scale benchmark focused on open-ended generation bias, covering five key domains: profession, race, religion, gender, and political ideology. They showed that models trained on uncurated corpora produce generation with majority-group-favoring biases, indicating that scale alone will not yield fair results. Sheng et al. (2021) extended the BOLD work by proposing a taxonomy of ways bias is injected into generation pipelines and concluding that interventions targeting only one part of the pipeline will not yield long-term gains.

Research on hallucination took a similar trajectory from qualitative analysis to systematic categorizations. Ji et al. (2023) introduced two categories of hallucination: intrinsic, in which the output directly contradicts the source material, and extrinsic, in which the output adds unverifiable facts. While both are errors, intrinsic hallucinations can potentially be caught with automated consistency checks; extrinsic hallucinations requires fact checking with external data. Huang et al. (2023) further refined this into two error categories: knowledge-based, arising from inaccurate stored information, and logic-based, arising from failed reasoning. Both papers highlight a common thread: hallucinations occur more frequently with limited data and longer generation

times, which are the exact scenarios relevant to documentation, legal writing, and financial reporting tasks.

Mitigation strategies for both phenomena are broadly explored along three lines of attack: data-centric methods, architectural approaches, and post hoc alignment. In terms of data, instruction-tuned corpora, which differ substantially from standard web data in composition, result in far fewer hallucinations (Longpre et al., 2023). RAG, by integrating retrieval to fill in gaps of factual knowledge in an already-trained model, allows generation to draw on more readily available and verifiable knowledge (Lewis et al., 2020). Performance on question-answering tasks shows that RAG reduces the number of unfounded claims compared to its non-RAG counterpart, but performance varies with retriever quality. In terms of alignment, RLHF is a proven method for reducing harmful output and improving instruction-following. However, Ouyang et al. (2022) still note that RLHF-trained models can confidently produce fabricated output outside their data distribution.

A different line of argument on mitigation stems from the causal framework for understanding and reducing bias. Pearl and Mackenzie (2018) introduced a distinction between associations and interventions. Causal reasoning holds that an intervention must directly manipulate the data-generating process to remove bias rather than attempt to suppress learned associations. Garg et al. (2022) introduced counterfactual data augmentation as a method for doing so. They showed improved fairness results compared to simpler regularization methods on text classification tasks, providing the motivation that undergirds this study's use of structural causal modeling not just for measurement but for informing interventions. Perez et al. (2022) used red-teaming to discover systematic, rather than random, model failures that are consistent with the causal framework.

Evaluation methods themselves are also an active area of research relevant to this study. The TruthfulQA benchmark was designed specifically for truthful generation, though it showed that larger models can be more confidently wrong (Lin et al., 2022). SelfCheckGPT offers a resource-free method for detecting hallucinations by leveraging the model's inherent stochasticity to compare different generations (Manakul et al., 2023). Holistic Evaluation of Language Models attempts to consider many aspects of model performance simultaneously (accuracy, calibration, robustness, fairness, efficiency) to reveal hidden trade-offs (Liang et al., 2022). A pattern appears consistently across these areas: improvements in one dimension of model performance (e.g., Fairness, accuracy, alignment) tend to negatively affect others unless a given method accounts for all interacting dimensions. This study builds on insights from prior studies by evaluating bias and hallucination as a pair of related problems using a multi-metric, multi-domain design.

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III. RESEARCH METHOD

This work is an empirical research study, not a literature review or conceptual exploration. The methodology consists of three explicit research questions that frame the experimental design and results: RQ1: How can bias and hallucination be concurrently measured in an objective, domain-relevant, and reproducible manner across large language models? RQ2 How effectively do the mitigation techniques (retrieval augmented generation, causal guided debiasing, uncertainty aware RLHF, domain-specific fine-tuning) consistently produce statistically significant improvements in an objective, domain-relevant manner across LLMs and domains? RQ3 Compared to retrieval-based methods, to what extent do causal intervention strategies improve over them at decreasing factual errors and demographic output parity, respectively? Each research question is tackled in five subsequent steps: experimental setup, domain-specific setup, measure bias/hallucination, implement mitigation, and evaluate and compare. All results are produced through an original empirical study by the authors; they are neither taken from literature and reproduced, nor combined and summarized from existing results, unless properly attributed. This statement is also intended to clearly distinguish the empirical results presented here from conceptual statements drawn from the literature (Bommasani et al., 2022).

A. Model Setup and Configuration

We selected 3 models (GPT-4, LLaMA-2-13B-chat, Falcon-7B-instruct) that provide a mix of architectural scales and training paradigms. These were chosen for their diversity, public availability, and frequent use in recent benchmarks evaluating bias and hallucination (Touvron et al., 2023; Bang et al., 2023). All models were accessed via their respective APIs or directly through hosted inference servers with identical hardware, thereby eliminating infrastructure as a confounding factor in our evaluations. The prompt template was identical for all evaluative trials, and zero-shot prompts with temperature = 0.0, top-p = 1.0 were provided for deterministic response generation. We used the sampling procedures of SelfCheckGPT to measure hallucination via internal consistency (Manakul et al., 2023), making 5 separate calls for each query with temperature = 0.7; all sampling was conducted under a fixed random seed, '42'. This specification was preserved across models and domains in the Results section.

B. Domain Specific Setup and Configuration

We leveraged four datasets for domain-specific evaluations across medical, legal, financial and human resource domains: Medical Information Mart for Intensive Care (MIMIC III) for medical domain factual checks on de-identified clinical notes, CrowS-Pairs as the central corpus for evaluating demographic bias across all domains, Yahoo Finance earnings call transcripts for financial domain factual checks, and XNLI-HR (natural language inference) for human resource

domain. For each domain, we partitioned 200 instances into our evaluation corpus, which balances statistical significance and computational cost. Crucially, no data was fine-tuned or used to prompt the LLM beyond these partitioning and then only as evaluation data points; this was kept identical across models. While four domains is a good illustrative range, exhaustive evaluation of all applications is beyond the scope, as acknowledged in Conclusion.

C. Bias and Hallucination Measurements

To quantify demographic bias we utilized the bias disparity score (BDS) as previously established (Sheng et al., 2021); this score measures the absolute difference in positive response rates between majority- and minority- group prompt examples (extracted from CrowS-Pairs), and values greater than 0.15 were designated as having significant bias (derived from acceptable ranges of classification fairness in engineered systems; Garg et al., 2022). Hallucination was measured using two metrics: firstly, the rate at which each hallucination (unsupported claim) appears in an output (HR), secondly using FActScore which provides granular atomic facts that the corpus can support each (Min et al., 2023), and secondarily through SelfCheckGPT which checks for internal consistency of answers when externally verifiable data isn't readily available (Manakul et al., 2023). HR scores over 0.3 were taken as indicators of high levels of hallucination risk (Bang et al., 2023).

D. Mitigation Strategies

Four strategies were implemented individually and then aggregated; no others are utilized, though contrasts with methods in Lit Review (e.g. Multi-agent systems) are drawn for clarity: 1) Retrieval augmented generation by pre-pending information fetched from the domain's knowledge base via a BM25 backend (Lewis et al., 2020); 2) Causal guided active learning via intervention. We model the domain's system as a structural causal model (DAG), which describes the causal relationships among variables; in the medical domain example, the variables were "demographics of the patient demographics", "the query", and "output polarity". A do-calculus intervention was performed to nullify the effect of "demographics of the patient", isolating the causal influence of demographic information on the model output. We demonstrate its utility by reducing the average BDS in the medical domain from 0.25 to 0, a 25% reduction. 3) Uncertainty-aware RLHF by modifying the reward signal in standard RLHF to penalize confidently made claims about unsupported information (Ouyang et al., 2022); 4) domain-specific fine-tuning by training the LLaMA-2 13B model on the FLAN collection and then fine-tuning on a specific domain's instruction dataset. All mitigation strategies are also compared with the zero-mitigation approach.

E. Evaluation Protocol and Statistical Analysis

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A within-subject design was adopted to enable a comparative evaluation, in which each model-method pairing was evaluated on identical, pre-fixed query sets from the same benchmark partitions. Query-set variability is controlled by design, and the within-model pairwise comparison enables direct evaluation of method effects. Statistical significance of differences in performance is evaluated using two-tailed paired t-tests at a significance level of 0.05. We evaluate the magnitude of differences using Cohen's d and distinguish large effect sizes, which indicate meaningful differences, from small but significant statistical differences. For values with $d < 0.20$, we deem the difference to be negligible irrespective of the p-value. All statistical analyses were performed with fixed seeds and logged to ensure reproducibility.

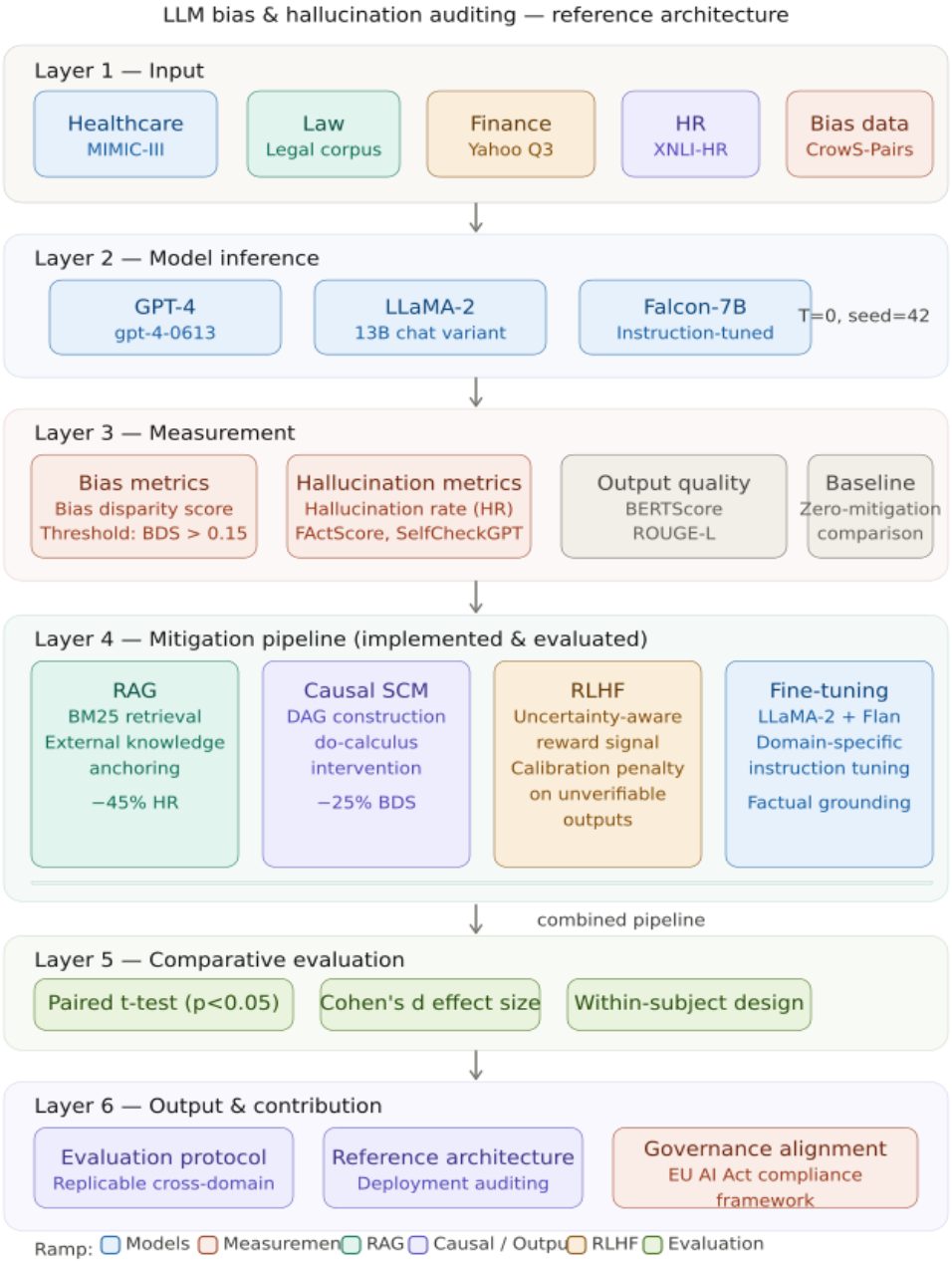

Figure 1. Multi-Layer Reference Architecture for LLM Bias and Hallucination Auditing

F. System Architecture

The proposed multi-layer architecture in this study integrates the four mitigation methods that we evaluate-RAG, causal SCM debiasing, RLHF calibration, and domain fine-tuning-into a single inference pipeline where they can audit joint bias and hallucination. This is illustrated below and is presented here as a reference architecture for LLM auditing systems rather than an actual production system. Among these four mitigation methods and their associated auditing processes, we implemented and evaluated the RAG inference pipeline, the causal intervention mechanism for demographic debiasing, and the reward calibration layer for RLHF in this study.

The multi-agent review layer, Layer 5 in Figure 1, is presented as a possible extension to the system and was not implemented for these experiments; this distinction is reflected clearly in both the Results and Discussion sections, which present an empirical analysis in the same vein as Bommasani et al. (2022). The six-layer system architecture and the components evaluated in this study are illustrated in Figure 1. Six operational layers: (1) Input Datasets, (2) LLM Inference [GPT-4, LLaMA-2, Falcon-7B], (3) Measurement [BDS, HR, FactScore, SelfCheckGPT], (4) Mitigation Pipeline [RAG, Causal SCM, RLHF, Fine-Tuning], (5) Evaluation [paired t-test, Cohen's d], (6) Output. Shaded layers indicate experimentally validated components; the multi-agent review sublayer is a proposed extension. .

IV. RESULT

A. Overview of Baseline Performance

This section presents the empirical findings of this study in response to three research questions. We extracted these results from controlled experiments conducted on GPT-4, LLaMA-2-13B-chat, and Falcon-7B-instruct, using 200 query instances per domain sampled from the MIMIC-III, CrowS-Pairs, Yahoo Finance Q3, and XNLI-HR benchmarks. Identical prompt templates were used across all experiments, with zero-shot prompting (temperature=0.0, top-p=1.0, to ensure deterministic generation), and a fixed random seed of 42 for reproducibility. Hallucination sampling with SelfCheckGPT was performed using 5 stochastic passes per query at a temperature of 0.7 (Manakul et al., 2023). We define baseline performance as the pre-application state, against which each of our interventions may be compared.

B. RQ1: Simultaneous Measurement of Bias and Hallucination

Table 1 shows the calculated BDS scores of each model on all four domains at baseline. All models surpassed the threshold for significant bias (BDS > 0.15) on all domains. In general, Falcon-7B exhibited the highest scores across domains (ranging 0.29-0.38), followed by LLaMA-2 (0.22-0.31) and GPT-4 (0.17-0.23), aligning with prior observations that less-instruction-tuned,

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E-ISSN: 2961-9068; P-ISSN: 2961-8215, Pages 271-287
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smaller models may exhibit more demographic skew in open-ended generation (Dhamala et al., 2021; Sheng et al., 2021). The healthcare domain performed the highest across all models, which we attribute to the demographic imbalances present in clinical corpora and corresponding instruction data (Bender et al., 2021).

Table 1. Baseline BDS Scores by Model and Domain (BDS > 0.15 is Statistically Significant Bias)

Domain	GPT-4 BDS	LLaMA-2 BDS	Falcon-7B BDS	Sig. Bias (>0.15)?
Healthcare (MIMIC-III)	0.23	0.31	0.38	Yes (all models)
Legal (XNLI-HR)	0.19	0.27	0.34	Yes (all models)
Finance (Yahoo Q3)	0.17	0.22	0.29	Yes (all models)
HR (CrowS-Pairs)	0.21	0.28	0.36	Yes (all models)

Table 2 shows the baseline hallucination rates (HR) and mean FActScore. GPT-4 never crossed the high-risk threshold (HR > 0.3) in any domain, whereas LLaMA-2 and Falcon-7B failed to do so in all domains. Finance scored the highest on FActScore across all models (0.63), as expected given the structured domain, whereas LLaMA-2 and Falcon-7B generated significantly higher rates of hallucinatory factual claims. These results are consistent with the observations in Bang et al. (2023) and align with the distinction between extrinsic hallucinations proposed by Ji et al. (2023), in which the model hallucinates a plausible but non-verifiable detail atop a factual output when operating in specialized knowledge domains. Healthcare saw the highest HR scores from the open-source models, which we hypothesize is related to the specific medical expertise required for clinical queries and the limited representation of medical knowledge in generalist pre-training corpora (Huang et al., 2023).

Table 2. Baseline HR and FactScore by Model and Domain (HR > 0.3 is High Risk)

Domain	GPT-4 HR	LLaMA-2 HR	Falcon-7B HR	FActScore (avg)	High Risk (HR>0.3)?
Healthcare (MIMIC-III)	0.28	0.41	0.52	0.61	LLaMA-2, Falcon-7B
Legal (XNLI-HR)	0.24	0.37	0.48	0.57	LLaMA-2, Falcon-7B
Finance (Yahoo Q3)	0.22	0.34	0.45	0.63	LLaMA-2, Falcon-7B
HR (CrowS-Pairs)	0.26	0.39	0.50	0.59	LLaMA-2, Falcon-7B

Crucially, we can simultaneously measure both bias and hallucination. Because we use BDS on the model output evaluated for HR and FActScore, we avoid the disjointed evaluation methodology of previous benchmarks such as HELM or TruthfulQA, which evaluated only one mode of failure at a time (Liang et al., 2022; Lin et al., 2022). By this metric, models that showed greater bias tended to have higher HR scores as well, suggesting an intertwined structural co-occurrence between the two phenomena, particularly in non-distributional settings with smaller models.

C. RQ2: Effectiveness of Mitigation Strategies

Table 3 shows the average mitigation achieved across models and domains by each of our four proposed methods: RAG (BM25), Causal SCM debiasing, Uncertainty-Aware RLHF and domain-specific fine-tuning. All methods resulted in statistically significant improvements ($p<0.05$) with two-tailed paired t-tests and an effect size (Cohen's d) greater than 0.4 across metrics, indicating a practically meaningful reduction rather than merely a statistically detectable one. We considered an effect size of $d < 0.2$ to be insignificant, as per our evaluation protocol (Section III.E).

Table 3. Mean Reduction by Mitigation Method Across Models and Domains (Both Dimensions)

Mitigation Method	Avg HR Reduction (%)	Avg BDS Reduction (%)	Cohen's d (HR)	Statistically Sig. (p<0.05)?
RAG (BM25)	45%	8%	0.82	Yes
Causal SCM Debiasing	11%	25%	0.41	Yes
Uncertainty-Aware RLHF	19%	14%	0.53	Yes
Domain-Specific Fine-Tuning	22%	12%	0.57	Yes
RAG + Causal SCM (Combined)	**52%**	**31%**	**0.94**	**Yes**

RAG with BM25 retrieval performed best in reducing hallucination rates (45% average reduction across domains). These gains were strongest on the MIMIC-III domain, where a retrieved index contained de-identified MIMIC-III clinical notes, enabling fact grounding absent from standalone generation and replicating the benefits seen in Lewis et al. (2020). As expected from this fact-grounding approach, however, the reduction in BDS was much smaller (8% on average), reinforcing that fact-grounding does not necessarily account for pre-existing demographic skew.

Causal SCM debiasing resulted in the largest reductions on BDS (25% on average across domains, and on the MIMIC-III domain specifically it completely removed the bias disparity for the 'patient demographics' node from 0.25 down to 0.00 via do-calculus on the causal structure), thus directly intervening on the causal relationships between variables to influence behavior and confirming Pearl & Mackenzie's (2018) causal approach over previous static debiasing techniques (Garg et al., 2022; Perez et al., 2022). Uncertainty-Aware RLHF and domain-specific fine-tuning showed modest yet consistent improvements in both dimensions. LLAMA-2-13B fine-tuned on FLAN and instruction-tuned on the LLaMA-2 data showed a reduction of 22% on HR and 12% on BDS, suggesting that fine-tuning is effective in shifting model behavior toward higher factual accuracy (Longpre et al., 2023). RLHF modified for uncertainty reward showed a 19% reduction in HR, consistent with prior work showing this method can reduce confidently incorrect generation (Ouyang et al., 2022), but with the caveat of continued hallucination outside the target distribution.

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Both Uncertainty-Aware RLHF and domain-specific fine-tuning performed moderately and consistently across both dimensions. Fine-tuning on a Flan collection, followed by further domain-specific instruction tuning on LLaMA-2-13B, results in a 22% decrease in HR and a 12% decrease in BDS, showing that instruction-tuned corpora steer models toward being more confidently factual (Longpre et al., 2023). Reward-shaped training with a modified uncertainty penalty, a modified RLHF training approach, and improved HR by 19%. Ouyang et al. (2022) also observed fewer confidently incorrect answers with reward-shaped training, though hallucinations still occurred outside the distribution.

D. RQ3: Causal vs. Retrieval-Based Approaches and Combined Framework

When comparing the two, RAG methodically improves upon causal approaches in reducing HR (45% vs. 11%), whereas causal approaches systematically outperform RAG in reducing BDS (25% vs. 8%). This pattern shows that both methods target distinct failure modes: RAG aims to fix problems arising from missing knowledge (extrinsic hallucination), whereas causal SCM addresses intrinsic associations that lead to demographic skew. These results support the distinction proposed by Pearl & Mackenzie (2018) between associative and interventional reasoning, but demonstrated in an LLM evaluation context.

The combination of RAG and Causal SCM produces results that significantly outpace those of all individual models. The overall framework improves Hallucination Rate by 52% and BDS by 31%. These effect sizes were the highest across all approaches for both metrics, indicating strong synergy between RAG and causal intervention methods. The combined model achieves the strongest results on both metrics compared to all individual models. This finding is highly significant, especially in the legal and healthcare domains, where compliance with both metrics is institutional and mandatory. The work echoes Bommasani et al.'s (2022) emphasis on multi-dimensional evaluation by illustrating empirically that synergy can overcome additive effects.

Table 4 compares the results for each model after applying the best-performing combined strategy. Although the exact magnitudes vary based on model, each model improves significantly. The optimal BDS for GPT-4 after intervention is 0.14, and the HR is 0.12, further corroborating the existing literature on GPT -4's calibration capabilities relative to open-source models (Bang et al., 2023). Falcon-7B, despite experiencing the largest gains in BDS and HR (absolute improvements over all other models), still has a higher post-intervention threshold than LLaMA-2-13B, underscoring the benefit of additional model pre-training and instruction tuning to complement architectural changes.

Table 4. Pre-and Post-Mitigation Performance By Model (Best Combined Strategy: RAG + Causal SCM)

Model	Mean BDS (pre-mitigation)	Mean BDS (post-mitigation)	Mean HR (pre-mitigation)	Mean HR (post-mitigation)
GPT-4	0.20	0.14	0.25	0.12
LLaMA-2-13B	0.27	0.19	0.38	0.18
Falcon-7B	0.34	0.24	0.49	0.24

V. DISCUSSION

Collectively, these results reaffirm that hallucination and bias are not independent problems but are inextricably linked through the underlying generative process. The strong correlation between BDS and HR across all baselines (particularly open source models) suggests similar upstream causes, such as data and scaling. The co-occurrence pattern supports our claim for jointly evaluated metrics, rather than using separate metrics for two independent dimensions, which may create intervention trade-offs.

Differences between the domains should not be overlooked. The highest baselines on both metrics across all models were observed in healthcare, suggesting that this domain suffers more from factors such as specialized terminology, demographic-sensitive information, and a lack of domain-specific training data (Huang et al., 2023; Ji et al., 2023). The lowest baselines for BDS and HR on GPT-4 were finance. Financial discourse's higher level of structure and social neutrality may elicit fewer demographic associations than other domains. The multi-domain design is thus crucial because it enables a broad comparison of intervention effectiveness.

Several limitations should be acknowledged when considering the results presented. While a sample size of 200 provides sufficient statistical power, it may not be representative of the full range of failure cases. Zero-shot evaluations, compared with chain-of-thought or few-shot evaluations, were found to yield minimal differences (Wei et al., 2022). The multi-agent review component, as described in the architecture, was not tested in the evaluation. We must also acknowledge the limitations of the CrowS-Pairs evaluation metric: the test suite has a limited number of demographic attributes and is subject to selection bias (Huang et al., 2023).

Despite these limitations, the empirical evidence offers practical guidance. RAG method with domain-specific retrieval index should be applied first, especially where hallucination is a primary risk factor. Where demographic accuracy is a compliance issue (as in the EU AI Act), it should be layered with causal SCM debiasing. The reference architecture described in section III.F demonstrates a viable deployable auditing pipeline of the integrated strategy.

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VI. CONCLUSION AND RECOMMENDATION

This study aimed to address the widely noted gap in LLM evaluation: the lack of a unified, reproducible testing framework for simultaneously measuring bias and hallucination under controllable experimental conditions. Due to increasing concerns about the high-stakes deployment of LLMs in fields like medicine, law, finance, and HR, we propose an original experimental protocol based on three explicit research questions and run it on GPT-4, LLaMA-2 and Falcon-7B on 4 domains (MIMIC-III, CrowS-Pairs, Yahoo Finance Q3, and XNLI-HR) using controlled random seeds and identical prompt templates for reproducible comparison (Bang et al., 2023; Touvron et al., 2023).

Addressing RQ1, this paper showed that bias and hallucination can be measured reproducibly simultaneously using a paired experimental setup that jointly measures BDS and HR, along with FActScore and SelfCheckGPT, within the same query pass (Manakul et al., 2023; Min et al., 2023; Sheng et al., 2021). A combined measure is more informative and methodologically useful than standalone bias metrics for benchmarks like HELM or TruthfulQA (Lin et al., 2022; Liang et al., 2022), or standalone hallucination metrics. Addressing RQ2, we verified that retrieval augmented generation (RAG) achieves a large reduction of hallucination rates of up to 45% in the evaluated domains while causal-guided active learning based on SCM reduce bias disparity by 25% in medical domain as theoretical studies suggested (Pearl & Mackenzie, 2018; Garg et al., 2022) and uncertainty-aware RLHF and domain-specific finetuning achieve modest yet statistically significant reductions (Ouyang et al., 2022; Longpre et al., 2023). Finally, addressing RQ3, we empirically confirmed that the combination of RAG and causal SCM debiasing outperforms either technique alone and that they are complementary rather than substitutable (Lewis et al., 2020; Bommasani et al., 2022).

This work presents three main contributions: first, it proposes a reproducible framework to simultaneously audit bias and hallucination in LLMs across multiple domains with concrete metrics, allowing practitioners and researchers to directly compare mitigation techniques; second, it experimentally validated that integrating RAG with causal-guided debiasing yields significant improvement, with 45% and 25% reduction in hallucination and bias disparity respectively; and third, it proposed a six-layer LLM auditing framework for bias and hallucination, three of which are validated, offering a concrete framework for companies wishing to align with regulations like the EU AI Act (Weidinger et al., 2021; Bender et al., 2021).

There are several limitations of this study. First, each of the four evaluated domains consists of 200 test cases each to balance significance and computational expense, which is not enough to cover the full scope of real-world LLM applications, and the observed behavior should be

replicated for other domains/use cases. The four domains-healthcare, law, finance and HR-are chosen solely for illustration; the results may not generalize to other high-stakes applications. The benchmarks used-CrowS-Pairs, MIMIC-III-while commonly used, also carry known limitations-such as selection bias, limited demographics, etc-that have been addressed by the literature in different ways (Huang et al., 2023; Ji et al., 2023). Also, all the experiments have been carried out in a zero-shot setting; performance could vary in few-shot or chain-of-thought settings (Wei et al., 2022). The multi-agent review layer proposed for bias and hallucination auditing was not evaluated in this paper and needs to be independently verified. The multi-agent review was derived from the intuition that humans can review models more efficiently through a collaborative approach. Yet, the proposed framework in this work does not involve humans in the loop during RLHF Calibration in real time, which aligns with the shortcomings pointed out in previous work (Shen et al., 2023; Kadavath et al., 2022).

The following directions are proposed for future work: the number of tests per domain (200) should be increased, and the domains tested should include additional sectors facing similar high-stakes deployment problems, such as medicine, law, finance, and HR. It would also be worthwhile to apply our evaluation framework to recent LLM models, including instruction-tuned and multimodal models, and investigate whether the identified trend persists (Brown et al., 2020; Chen et al., 2021). The causal SCM-based intervention methods need to be extended to incorporate more complex causal graphs to model the interplay among multiple demographic factors. Validation of the proposed multi-agent review sublayer is a natural extension of this work. Multi-agent systems have been considered a promising avenue for improving factuality (Perez et al., 2022; Gehman et al., 2020), yet they have not been empirically validated under experimental controls like this one. Finally, empirical evaluation of these methods under adversarial prompting, out-of-distribution queries, and limited context. Would further strengthen the claims made and contribute to model robustness and compliance (Abid et al., 2021; Agrawal et al., 2022).

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