Bias Spillover in Language Models: A Review of Political Alignment, Regional Fragility, and Multi-Axis Risks

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Abstract

Efforts to mitigate social bias in large language models (LLMs) often address individual dimensions such as gender or political ideology in isolation. However, interventions targeting one axis can unintentionally influence others, a phenomenon we term bias spillover. This paper presents a structured review of over 80 studies, synthesizing empirical and theoretical evidence of cross-axis interference in model behavior. We identify four core mechanisms that drive spillover, including representational entanglement and conflicts introduced during fine-tuning, and we clarify the distinction between co-occurring biases and causal spillover. Our analysis reveals major limitations in current auditing practices, including the lack of standardized tools for measuring intersectional effects and limited coverage of non-Western and multilingual contexts. In response, we introduce a typology of auditing frameworks and recommend mitigation strategies that account for entangled social representations. These findings underscore the need for spillover-aware evaluation and debiasing approaches that move beyond isolated fairness metrics and reflect the complexity of real-world sociopolitical contexts.

1 Introduction

The rise and rapid advancement of large language models (LLMs) has fundamentally changed language technologies (Brown et al., 2020; Devlin et al., 2019; Raffel et al., 2020). With the ability to generate human-like text, as well as adapt to a wide array of natural language processing (NLP) tasks, the impressive capabilities of these models have initiated a paradigm shift in the development of language technologies. Instead of training task-specific models on relatively normalsize datasets, researchers and practitioners increasingly rely on LLMs as foundation models that can be fine-tuned or prompted to perform downstream tasks (Bommasani et al., 2021). Even without fine-tuning, foundation models now offer few- or zero-shot capabilities across a wide range of tasks such as classification, question-answering, reasoning, and information extraction (Brown et al., 2020; Kojima et al., 2022; Liu et al., 2023; Radford et al., 2019; Wei et al., 2022; Zhao et al., 2021).

Lurking beneath these technological successes is the persistent risk of social harm. LLMs are typically trained on massive, largely uncurated Internet-scale datasets, inheriting and reproducing stereotypes, ideological distortions, and exclusionary language that disproportionately affect marginalized groups (Bender et al., 2021; Dodge et al., 2021; Sheng et al., 2021). These harms often reflect what is broadly referred to as *social bias* - the systematic disparity in model behavior towards different demographic or ideological groups, arising from historical and structural asymmetries (Benjamin, 2020; Blodgett et al., 2017; Hutchinson et al., 2020; Mozafari et al., 2020; Sap et al., 2019; Sheng et al., 2019).

Prior work has documented the presence of such biases along many social axes, most notably gender (Blodgett et al., 2017) and political ideology (Liu et al., 2022). However, these two domains are often studied in isolation, each with their own datasets, taxonomies, and evaluation protocols. Gender bias is typically measured through occupational associations or pronoun resolution, whereas political bias is often evaluated via alignment with ideological statements or framing of issues. As a result, our understanding of how these biases might interact either during model training or evaluation, remains underdeveloped.

While several comprehensive reviews of social bias in large language models (LLMs) already exist (eg.,Gallegos et al. (2024a), our goal is narrower and more focused: we examine how political bias interacts with other social dimensions, especially gender, race, and religion in ways that are often unintentional and under reported. Our central contribution is the concept of *bias spillover*, which refers to the phenomenon where interventions targeting one axis of bias (e.g., political ideology) inadvertently induce shifts along another (e.g., gender or racial representation). This matters because fairness interventions that ignore such inter dependencies may reinforce or create new harms. For instance, political fine-tuning has been shown to alter emotional tone and moral framing, while gender balancing in generative models can distort age distributions. In this review, we analyze recent methods and benchmarks that either directly or incidentally reveal bias spillover effects, highlight key gaps in current auditing practices, and argue for more interaction-aware evaluation frameworks. Rather than offering a broad taxonomy, we aim to surface the methodological blind spots that prevent current tools from capturing spillover and intersectional risk in LLM behavior.

2 Political Bias in LLMs

2.1 Definitions and Typologies of Political Ideology

Political bias is typically defined with respect to specific ideological axes. The most common is the unidimensional *left–right* spectrum, where "left" often connotes progressive or egalitarian positions, and "right" typically denotes conservative or hierarchical orientations Feng et al. (2023). However, this one-dimensional framing can oversimplify complex political views, especially on issues like state intervention, individual freedoms, or identity politics. Multidimensional typologies such as the *Political Compass* introduce a second axis, often labeled as *libertarian–authoritarian*, to capture the interplay between economic and social ideologies Feng et al. (2023). More recent approaches extend this to data-driven ideological spaces derived from political text corpora or survey embeddings Röttger et al. (2024).

2.2 Methods for Political Bias Auditing

Political bias auditing in large language models (LLMs) includes both behavioral evaluation and architectural intervention. Table 1 outlines major strategies, ranging from direct testing to fine-tuning. These approaches differ in terms of introspection depth, bias assumptions, and robustness to model evasion. Direct testing methods apply standardized political alignment quizzes (e.g., Political Compass) to place models along ideological axes. While these consistently reveal social left-leaning tendencies in commercial LLMs, they suffer from calibration flaws, oversimplified spectra, and constrained response formats (Rottger et al., 2024). Indirect and task-based methods like PRISM (Azzopardi & Moshfeghi, 2024) instead use implicit cues in generative prompts to uncover latent ideological stances, providing better resistance to model evasion.

User perception studies, where annotators rate the political slant of model outputs, often confirm perceived left-leaning biases even among left-leaning raters (Rottger et al., 2024). Content and style analysis decomposes outputs into thematic and rhetorical dimensions to detect subtle framing patterns (Bang et al., 2024), while target-oriented sentiment classification substitutes political names into fixed prompts to reveal sentiment asymmetries (Liu et al., 2021b). Experimental manipulation through fine-tuning on partisan corpora allows for direct ideological steering. As shown in Table 2, parameter-efficient fine-tuning (PEFT) methods such as LoRA, QLoRA, and Direct Preference Optimization (DPO) have been applied to align models like LLaMA-2/3 and Mistral with curated ideological corpora (Agiza et al., 2024; Stammbach et al., 2024; Chalkidis & Brandl, 2024).

However, political bias auditing remains methodologically fragmented, with significant variance across dataset design (e.g., source corpus, party-labeling granularity), alignment objectives (e.g., stance conditioning vs. preference modeling), and evaluation metrics (e.g., sentiment shift, moral tone, factuality). Among these, the absence of shared datasets and benchmarking protocols presents the most serious barrier to generalizability. Variability in PEFT methods complicates reproducibility, but the inconsistency in evaluation pipelines including incompatible taxonomies and metrics makes cross-study comparisons especially difficult.

Table 1: Overview of methods for political bias auditing in LLMs

Method	Description and key features
Direct testing approaches	Administers standardized political orientation tests (e.g., Political Compass Test, Political Spectrum Quiz). Places models on ideological axes (economic/social). Consistently finds left-leaning tendencies in commercial LLMs on social issues. **Limitations:** Test calibration bias, constrained response formats, and evasion mechanisms reduce external validity (Rottger et al., 2024).
Indirect and task-based approaches	Uses techniques like PRISM (Preference Revelation through Indirect Stimulus Methodology), where models generate essays or content under assigned roles or prompts. Reveals latent ideological stances without explicit questioning. More robust against refusal or evasion (Azzopardi & Moshfeghi, 2024).
User perception studies	Human raters evaluate the political slant of LLM responses to politically charged questions. Focuses on perceived bias over internal representations. Studies consistently show LLMs are perceived as left-leaning, including by left-leaning annotators (Rottger et al., 2024).
Content and style analysis	Decomposes bias into *content* (what is said) and *style* (how it's said). Analyzes emphasis, rhetorical framing, tone, and lexical choices to uncover subtle and structural political alignment Bang et al. (2024).
Target-oriented sentiment classification	Inserts names of left- and right-leaning political figures into identical sentences and measures sentiment polarity. Highlights differential treatment across political identities (Liu et al., 2021b).
Experimental manipulation approaches	Fine-tunes models on politically biased corpora (e.g., left/right news). Assesses changes in alignment post-intervention. PoliTune is a representative framework for systematic tuning and measurement (Agiza et al., 2024).

However, the field remains technically fragmented. There is no consistent protocol regarding the choice of alignment objectives (e.g., stance prediction vs. preference modeling), fine-tuning techniques (e.g., DPO vs. supervised instruction tuning), or evaluation setups. For instance, Stammbach et al. (2024) evaluate supervised fine-tuning (SFT), Direct Preference Optimization (DPO), and Monolithic Preference Optimization (ORPO), finding ORPO to yield the most diverse and human-aligned generations in a Swiss political context, while DPO underperforms without additional tuning (Table 2). In contrast, Chalkidis & Brandl (2024) employ only SFT with LoRA to adapt models to European Parliament party ideologies and report effective alignment particularly for ideologically consistent parties, suggesting SFT alone may suffice in some settings. These mixed results imply that no single PEFT method is consistently preferred across political alignment tasks. A broader snapshot of this methodological heterogeneity is shown in Table 2, which compares datasets, model sizes, and alignment techniques across recent studies. Overall, the diversity in model scales, data sources, and annotation schemes makes it difficult to draw generalizable conclusions.

3 Political Framing in LLMs: The case of US and EU

3.1 Differences between US and EU in political labeling and ideological structure

The political landscape in the United States is predominantly characterized by a binary party system, composed mainly of the Democratic and Republican parties. This structure encourages a relatively linear ideological framework most commonly framed as liberal versus conservative which simplifies political alignment and audit design for large language models (LLMs). In contrast, the European Union (EU) encompasses a far more complex and multipolar political spectrum. Political representation in the EU is structured around multiple *euro-parties* (transnational political groups in the European Parliament), such as the European People's Party (EPP), the Progressive Alliance of Socialists and Democrats (S&D), the Greens–European

Table 2: Partisan political datasets and methods used for fine-tuning conversational models

Key characteristics / purpose	Method
Aligning LLMs with diverse political viewpoints: Party-labelled German stance datasets (Stammbach et al., 2024)	LoRA (r=8) adapters per party on LLaMA-3 8B; ORPO alignment
PoliTune: Curated left/centre/right policy prompts with synthetic preferences; ablation of data vs. method (Agiza et al., 2024)	LoRA on LLaMA-3 70B and Mistral-7B; DPO
LLaMA meets EU: 87k Euro-Parliament speeches labelled by political group (Chalkidis & Brandl, 2024)	LoRA adapters per party on LLaMA-2-13B-chat
Speaker attribution QLoRA: German Bundestag debates (2017–2021) (Bornheim et al., 2024)	QLoRA on LLaMA-2-7B for GermEval 2023 speaker-role tagging

Free Alliance (Greens/EFA), and The Left in the European Parliament – Nordic Green Left (GUE/NGL) (Chalkidis & Brandl, 2024). These parties differ not just along the socio-economic left–right axis but also across other ideological dimensions including environmentalism, civil liberties, and attitudes toward EU integration (ranging from pro-EU to Eurosceptic and anti-EU). As a result, LLMs pretrained on US-centric corpora often fail to capture the ideological diversity present in EU contexts. Moreover, while US political parties tend to be more ideologically cohesive, EU parties particularly large coalitions like the EPP and S&D are often "big tents" encompassing a wide range of internal viewpoints (Stammbach et al., 2024; Chalkidis & Brandl, 2024). Table 3 summarizes the differences. This heterogeneity poses significant challenges for political bias audits and alignment in LLMs. Region specific fine-tuning, such as adapting models on European parliamentary speeches, becomes essential to accurately reflect the EU's pluralistic political environment. Without such adaptations, LLMs like ChatGPT and LLaMA-based models have been shown to default toward liberal or progressive narratives that align more closely with left-leaning euro-parties, such as Greens/EFA and S&D, thereby missing the ideological nuances of the broader European political spectrum (Exler et al., 2025; Chalkidis & Brandl, 2024).

Table 3: Differences in political labeling and ideological structure between the US and EU

Key differences	US vs. EU comparison
Political system structure	**US:** Binary party system (Democrats vs. Republicans). **EU:** Multiparty system with coalition-based euro-parties across many ideological axes (Chalkidis & Brandl, 2024).
Ideological dimensions	**US:** Primarily single-axis (liberal vs. conservative). **EU:** Multidimensional: economic (left–right), civil liberties (liberal–authoritarian), EU integration (pro- vs. anti-EU) (Chalkidis & Brandl, 2024).
LLM bias observations	**US:** ChatGPT and similar models lean liberal/progressive (Stammbach et al., 2024; Feng et al., 2023). **EU:** LLMs align more with GREENS/EFA and S&D positions unless specifically adapted (Chalkidis & Brandl, 2024).
Party cohesion	**US:** Parties are generally more internally cohesive. **EU:** Major euro-parties (e.g., EPP, S&D) are "big tents" with wide internal ideological range (Chalkidis & Brandl, 2024).
Audit and adaptation needs	**US:** Bias audits based on US data and spectrum are directly applicable. **EU:** Requires contextual and region-specific fine-tuning to reflect political diversity (Chalkidis & Brandl, 2024).

3.2 Challenges in Transferring Bias Audits Across Regions

Bias auditing methods developed for U.S.-centric political contexts (e.g., Feng et al. (2023)) often do not generalize well to multilingual and ideologically complex regions such as the European Union (EU). Large language models (LLMs), including ChatGPT and LLaMA variants, are typically trained on English-language corpora that reflect American socio-political norms, leading to poor performance on region-specific political tasks. Chalkidis & Brandl (2024) demonstrate that instruction-finetuned LLMs refuse to answer prompts from the EUANDI questionnaire which is a political alignment tool for EU citizens due to their alignment with default safety and neutrality policies. To elicit responses, users must "jailbreak" the models i.e., modify the prompt phrasing in ways that circumvent built-in refusal mechanisms and enable the model to take a stance on politically sensitive issues. Even after such intervention, the models tend to favor ideological positions associated with Greens/EFA or S&D, while underrepresenting others such as EPP or ID, revealing persistent alignment biases. Similarly, Stammbach et al. (2024) show that ChatGPT generates nearly identical liberal responses for Swiss parties across the political spectrum, ignoring key distinctions. These findings illustrate the risks of applying binary U.S.-style audit frameworks to the EU's multiparty, multilingual context. Additionally, Feng et al. (2023) show that political biases embedded in pretraining data propagate through to downstream tasks, reinforcing polarization and fairness gaps. Altogether, this underscores the necessity for localized, culturally aware bias audits and targeted fine-tuning when deploying LLMs beyond the U.S. context.

4 Understanding Spillover Bias in LLMs

4.1 Empirical Observations and Definition

Most interventions in fairness and bias mitigation are designed with a single axis in mind such as race, gender, or political ideology. However, language models operate over richly entangled social representations, and modifying behavior along one axis can have unintended and sometimes compounding effects on others. This phenomenon, which we term *spillover*, occurs when efforts to mitigate bias for one group inadvertently introduce or exacerbate harms for others. For example, attempts to reduce gender bias may skew age representation (Shukla et al., 2025), or political fine-tuning may shift not only ideological alignment but also emotional and moral tone (He et al., 2023). These effects are not merely technical artifacts but signal deeper entanglements in how LLMs encode and express social meaning.

We define bias spillover as a phenomenon where mitigating bias along one social axis (e.g., political ideology) unintentionally alters model behavior on another (e.g., gender or race). Table 4 summarizes four mechanisms that contribute to this effect. First, during pretraining, LLMs encode socially distinct attributes in entangled subspaces, making isolated modification difficult. Marjieh et al. (2025) show a similar representational overlap for numeric and symbolic inputs. Second, fine-tuning introduces competing objectives: supervised fine-tuning (SFT) may enforce fairness, while direct preference optimization (DPO) aligns with user values. Chen et al. (2025) formalize this as a safety–capability trade-off. Third, LoRA-based updates affect shared layers across modalities, so interventions on one bias axis may propagate globally Hsu et al. (2025). Fourth, intersectional biases can emerge even when single-axis audits show neutrality; Souani et al. (2024) detect such hidden effects using their HInter framework.

It is important to distinguish co-occurrence from true spillover: the former refers to the presence of multiple biases in a model, whereas the latter denotes a causal relationship, where an intervention aimed at mitigating one type of bias actively causes a change in another. Without this causal link, intersectional disparities may still exist, but cannot be directly attributed to a spillover effect. Foundational studies on pretraining dynamics and latent representations (Devlin et al., 2019; Raffel et al., 2020; Bommasani et al., 2021) reinforce the importance of understanding such spillover as a systemic risk in model alignment. As summarized in Table 5, recent empirical work across a range of models and datasets reveals that such spillover effects are pervasive, even in studies not explicitly designed to investigate them. The political axis, in particular, emerges as a central node, influencing or being influenced by multiple identity dimensions such as race,

Table 4: Mechanisms contributing to bias spillover in language models

Bias spillover mechanism	Representative evidence and studies
Entangled embeddings during pretraining: Representations of social concepts such as race, gender, and ideology are embedded in shared subspaces, making it difficult to modify one without affecting others.	Marjieh et al. (2025) show representational blending in LLMs; similar entanglement across social concepts leads to unintended co-modifications.
Fine-tuning objective conflicts: Different fine-tuning phases (e.g., SFT vs. DPO) may introduce opposing gradients, causing trade-offs between safety, bias mitigation, and preference alignment.	Chen et al. (2025) formalize safety–capability trade-offs during tuning; aligning to one objective can inadvertently amplify bias elsewhere.
LoRA spillover via shared layers: Parameter-efficient fine-tuning (LoRA) modifies shared attention layers, so adaptations for one axis (e.g., gender) may affect others (e.g., race).	Hsu et al. (2025) find increased safety risks from LoRA due to shared representations, warning of unintended bias propagation.
Intersectional bias and multi-axis interactions: Models may appear unbiased on single attributes but show strong bias at intersections (e.g., Black women). Spillover arises when mitigation ignores these combinations.	Souani et al. (2024) develop HInter to uncover hidden intersectional bias; find 16.6% of inputs trigger undetected multi-attribute bias.

gender, language, and emotion. This highlights the need to move beyond siloed fairness interventions toward more holistic, interaction-aware evaluation.

4.2 Literature Coverage and Gaps

While the literature has steadily expanded to include more complex, intersectional analyses, coverage remains uneven. Studies like Chen et al. (2023), Forcada Rodríguez et al. (2024), and An et al. (2025) explicitly examine how interventions across one axis affect outcomes on others, revealing persistent interaction risks. Others, such as Naous et al. (2024) and Exler et al. (2025), uncover these dynamics as emergent properties rather than as targeted inquiry. However, few works systematically benchmark models on *multiple axes simultaneously*, especially beyond binary gender or U.S.-centric racial categories. Moreover, existing frameworks like CPAD (Dai et al., 2024) or CMBE (Sun et al., 2025) often rely on simplified categorical variables, missing more nuanced sociocultural intersections. Interventions like DAM (Kumar et al., 2023) and MAT-Steer (Nguyen et al., 2025) show promise in mitigating interference, but the broader implications of cross-attribute entanglement remain underexplored.

5 Global Blind Spots: Bias Spillover in Non-Western Contexts

Despite the proliferation of LLM research, the overwhelming majority remains anchored in Western linguistic, political, and social contexts. As a result, fundamental dimensions of political discourse, that ranges from the intersection of caste and religion in India, to gendered cultural norms in Southeast Asia, to state censorship in China, are poorly modeled and often distorted in mainstream LLMs.

5.1 Caste and Religion are Inseparable from Politics

In India, caste and religion are central to sociopolitical identity but are often overlooked in mainstream bias audits. The Indian-BhED dataset reveals that models like GPT-3.5 display stronger caste- and religion-based biases than gender or race-based ones, exposing the limits of Western-centric fairness metrics (Khandelwal et al., 2024). Additionally, demographic-matched evaluations show that LLMs tend to align with dominant religious ideologies, such as Hindu majoritarianism, regardless of prompt variation (Shankar et al., 2025).

Table 5: Bias spillover effects from debiasing interventions; starred methods introduce strategies to reduce intersectional risk

Intervention and observed spillover effect	Models and datasets evaluated	Spillover type
I. Single- and multi-axis debiasing methods		
Fairness-MultiAttr (Chen et al., 2023): Single-axis fairness improvements increased racial and age bias.	Logistic regression, random forest, XGBoost, BERT on Adult, COMPAS, MEP15/16	Gender → Race, Age
CPAD (Dai et al., 2024): Multi-attribute supervision outperformed single-axis debiasing.	BERT, RoBERTa on SST-2, MRPC, QQP with gender/race annotations	Gender → Race
CMBE* (Sun et al., 2025): Causal subtraction failed to resolve nuanced intersectional biases.	Vicuna-13B, GPT-3.5 on Multi-Bias Benchmark (gender, race, religion, age, sentiment)	Gender → Race, Religion, Age
DAM (Kumar et al., 2023): Adapter fusion preserved prior biases unless re-tuned.	RoBERTa-base on StereoSet, CrowS-Pairs, MNLI, SST-2	Gender → Race
Knock-on analysis (Nizhnichenkov et al., 2023): All debiasing methods induced new cohort gaps.	Adult, German Credit datasets	Any → Cohort gaps
II. Prompt- or instruction-based interventions		
MAT-Steer* (Nguyen et al., 2025): Orthogonal vector steering reduced attribute interference.	LLaMA-2-70B, Mistral-7B on TruthfulQA, BoolQ, open-ended tasks	Multi-Attr → Reduced interference
Multilingual occupation recommendations* (Forcada Rodríguez et al., 2024): Nationality shifted gender bias in job advice.	GPT-3.5, GPT-4 with prompts in Spanish, English, Wounaan	Nationality → Gender
Neutral prompts with social cues (Liu et al., 2021a): Cues elicited partisan completions despite neutrality.	GPT-2 on prompts with gender, location, topic variations	Demographic cue → Political
Political fine-tuning (He et al., 2023): Altered moral and emotional tone in addition to stance.	Instruction-tuned GPT on political tweets	Political → Emotion, Morality
III. Generative and multimodal bias experiments		
Intersectional sensitivity (Shukla et al., 2025): Gender balancing distorted age demographics.	Stable Diffusion 1.4 on musician prompts	Gender → Age
Western cultural bias in Arabic outputs (Naous et al., 2024): Western norms overrode local contexts.	GPT-4, JAIS-Chat on CAMeL for NER, generation, sentiment	Culture → Religion, Language
Larger models = more political skew (Exler et al., 2025): Political bias increased with model size.	Wahl-O-Mat task; LLaMA-2, Mistral, DeepSeek	Model scale → Political alignment
Fairness for women, racial penalty for Black men (An et al., 2025): Gender fairness coincided with race-based penalties.	GPT-3.5, GPT-4o, Claude, Gemini on 361k synthetic resumes	Gender → Race

This homogenization raises ethical concerns about how LLMs may reinforce political or moral narratives in culturally sensitive settings.

5.2 Regional Specificities Are Foundational

Arab-centric red teaming shows that models like GPT-4 and LLaMA 3.1 often reflect Western framings, exhibiting bias in contexts like terrorism and women's rights (Saeed et al., 2024). Geopolitical inconsistencies are also evident in bilingual outputs—for example, English prompts about China yield more critical responses than Chinese ones (Zhou & Zhang, 2024). In Africa, LLM performance varies with institutional language support; models underperform on many indigenous languages, reflecting deeper infrastructural and political marginalization (Adebara et al., 2025).

Table 6: Non-Western bias dimensions and relevance to political bias auditing

Dimension	Political link	Spillover type	Audit need
Caste (India)	Aligns with Hindu majoritarian or caste-hierarchical ideologies embedded in political narratives (Khandelwal et al., 2024).	Skews gender, socioeconomic status, and religious representation (e.g., anti-Dalit, anti-minority bias).	Use Indian-BhED; include intersectional metrics for caste, religion, and gender.
Religion (India, Arab world)	Reinforces dominant religious ideologies (e.g., Hindu majoritarianism, anti-Muslim narratives) tied to political stances (Shankar et al., 2025; Saeed et al., 2024).	Amplifies gender and ethnic stereotypes (e.g., Muslim women as oppressed).	Region-specific religious alignment tests; evaluate for bias spillover.
Language (Africa)	Favors institutionally supported languages aligned with dominant political groups (Adebara et al., 2025).	Marginalizes ethnic and regional identities; underrepresents local voices.	Develop multilingual benchmarks for unsupported languages; include cultural context analysis.
Gender norms (Southeast Asia, Japan)	Reinforces conservative or nationalist ideologies around traditional gender roles (Gamboa & Lee, 2024; Nakanishi et al., 2025).	Exacerbates religious or ethnic stereotypes, especially anti-queer bias.	Use localized gender frameworks; design culturally tailored prompts.
Geopolitical framing (China, Arab regions)	Reflects Western framings or internal censorship aligned with political agendas (Zhou & Zhang, 2024; Saeed et al., 2024).	Distorts cultural or religious narratives (e.g., anti-Arab bias).	Use bilingual and region-specific audits; check for narrative consistency.

5.3 Western Gender Templates are Misapplied

When adapted to Filipino, benchmarks like CrowS-Pairs and WinoQueer expose the failure of binary gender templates in Southeast Asian contexts (Nangia et al., 2020; Felkner et al., 2023; Gamboa & Lee, 2024). Even with localized data, models reproduce anti-queer and sexist content. Similarly, Japanese LLMs exhibit very low refusal rates for stereotype-triggering prompts, producing more toxic outputs than their English or

Chinese counterparts (Nakanishi et al., 2025). Tailored prompts often worsen stereotyping, revealing that prompt tuning alone is insufficient to mitigate these harms.

5.4 Non-Western Bias Dimensions and Political Auditing

Table 6 outlines how caste, religion, language, and gender norms intersect with political ideology in non-Western contexts. These examples illustrate the need for localized, intersection-aware auditing frameworks to avoid spillover effects and ensure fairer LLM behavior across global sociopolitical landscapes. The following examples illustrate region-specific intersections but are not meant as exhaustive political analyses. We highlight them to underscore the need for culturally grounded audits, while recognizing the depth of local expertise required for full treatment.

6 Summary and Future Recommendations

This review has highlighted how political bias in large language models (LLMs) often interacts with other social dimensions such as gender, race, religion, and geography, resulting in complex and sometimes unintended spillover effects. These entangled dynamics complicate both the auditing and mitigation of such biases, especially when standard pipelines address only single-axis fairness. To move toward more systematic, comparable, and responsible bias evaluations, we outline two parallel needs: a standardized template for bias spillover auditing, and clearer pathways for selecting mitigation strategies.

6.1 Toward a Spillover-Aware Auditing Template.

Auditing political bias in LLMs remains fragmented and often narrowly scoped. Existing evaluations vary across alignment objectives (e.g., stance vs. preference modeling), fine-tuning techniques (e.g., SFT, DPO, ORPO), and model scales, leading to inconsistent findings and limited generalizability. Compounding this issue is the common practice of auditing single identities in isolation, which neglects real-world contexts where multiple attributes intersect. The phenomenon of bias spillover where an intervention on one axis unintentionally alters model behavior on another—demands a more holistic approach.

We propose the adoption of a spillover-aware auditing template that emphasizes intersectionality and causal sensitivity. As summarized in Table 7, recent tools such as HINTER (Souani et al., 2024), HolisticBias (Smith et al., 2022), and SAGED (Guan et al., 2024) are promising in this regard. These frameworks enable structured probing of model outputs under multiple identity conditions, support disparity scoring across axes, and facilitate both qualitative and quantitative tracing of harm. By combining prompt-based perturbations, comparative generation, refusal classification, and longitudinal tracking, such methods help reveal spillover dynamics that conventional benchmarks might overlook. Future work should prioritize comparative evaluations of these tools to determine which combinations most robustly detect multi-axis harms in both open-source and black-box settings.

6.2 Mitigation Strategies and Debiasing Outlook

While auditing tools surface issues, they do not resolve them. Effective mitigation requires strategies that are spillover-aware and sensitive to the complexity of model representations. A growing body of work demonstrates that single-axis fairness interventions can inadvertently worsen biases along other dimensions especially when updates affect shared model parameters, as with LoRA or full fine-tuning. This reinforces the need for debiasing techniques that either isolate updates to targeted subspaces or explicitly model cross-axis interactions. Several promising directions are emerging. Techniques such as orthogonal steering e.g., MAT-Steer (Nguyen et al., 2025) attempt to control attribute directions without inducing interference. Causal mediation approaches e.g., CMBE (Sun et al., 2025) aim to identify and subtract bias-relevant components in representation space, though these often struggle with nuanced intersections. Adapter-based modular debiasing (Kumar et al., 2023) allows for incremental updates but may preserve legacy biases unless fine-tuned jointly. Importantly, many such methods lack unified evaluation pipelines, making their comparative utility unclear.

Table 7: Auditing methods for detecting identity entanglement and potential bias spillover in LLMs

Method	Axes covered	Spillover?	Strategy and utility
EQUITBL (Devinney et al., 2020b;a)	Gender, race, class	Partially	Semi-supervised topic modeling (open source); supports interpretive audits of representational harm across identity axes.
Refusal classification (Devinney et al., 2024)	Religion, race, gender	No	Rule-based audit (closed models); flags refusal patterns linked to identity and latent risk attribution.
Template phrase variation (Devinney et al., 2024)	Any (template-dependent)	Partially	Probing via controlled prompt swaps (open/closed); surfaces output shifts due to identity-bearing noun variation.
Comparative text generation (Ma et al., 2023)	Gender, race, orientation	Yes	Controlled generation (open/closed); compares responses across identity pairs to reveal interaction effects.
Prompt-based probing (Ma et al., 2023)	Gender, religion	Partially	Probing using stereotype-triggering prompts (open/closed); exposes compliance under social cue conditioning.
Qualitative case studies (Devinney et al., 2024)	Race, gender, orientation	No	Manual narrative analysis (open/closed); detects erasure, stereotype framing, and cultural invalidation.
Intersectional harm tracing (HInter) (Souani et al., 2024)	Race, gender, orientation	Yes	Statistical + contrastive framework (open/closed); surfaces hidden harms from entangled identity features.
HolisticBias (Smith et al., 2022)	13 identity axes	Yes	Structured descriptor scoring (open source); supports fine-grained analysis of intersectional bias with broad coverage.
BiasOutOfTheBox (Kirk et al., 2023)	Gender, race, age	Partially	Curated prompt suite (open/closed); detects subtle shifts in generation due to identity intersections.
SAGED (Guan et al., 2024)	Political, gender, race	Yes	Modular probing and scoring (open source); evaluates fairness across socio-political and demographic axes.

Rather than propose a definitive method, we recommend that researchers draw on existing survey work to understand the landscape of debiasing techniques. For instance, Gallegos et al. (2024b) provide an empirical comparison of mitigation methods across models and datasets; and Ranaldi et al. (2024) discuss challenges in mitigating social biases during generation. These resources are vital for matching debiasing methods to specific audit outcomes and deployment constraints. We also call for more publicly available datasets with labeled political and identity attributes, as well as standardized fairness metrics that track both direct and collateral effects of interventions.

6.3 Limitations and Future Work

This review has focused on open-source models and publicly documented interventions. Closed-source systems remain challenging to analyze due to lack of transparency, though black-box probing and perception-based evaluations provide partial alternatives. Additionally, our literature base is skewed toward English-language and Western-centric studies, limiting our understanding of how political and identity-related biases manifest globally. Expanding future audits to include non-Western contexts and low-resource languages is critical to ensure that fairness research does not perpetuate the very asymmetries it seeks to address.

Broader Impact Statement

This review of bias spillover in LLMs reveals risks of unintended harms, as interventions on one bias axis (e.g., political ideology) can exacerbate others (e.g., gender, caste). Such spillover may reinforce inequities, like caste discrimination in India or linguistic marginalization in Africa, particularly in public-facing AI systems. Politically skewed LLMs could distort discourse or amplify polarization, especially in non-Western contexts where cultural nuances are underrepresented. Our proposed spillover-aware auditing template and tools (e.g., HInter, SAGED) aim to mitigate these harms by promoting intersectional evaluations. However, data scarcity and computational costs may limit adoption. By advocating for localized audits and global data equity, this work seeks to foster fairer AI that respects diverse sociopolitical landscapes, enhancing trust and inclusivity. Future efforts must prioritize non-Western contexts to avoid perpetuating global asymmetries.

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