Sociodemographic Bias in Language Models: A Survey and Forward Path

Vipul Gupta[1] **Pranav Narayanan Venkit**[2] **Shomir Wilson**[2] **Rebecca J. Passonneau**[1]
[1] Depart. of Computer Science & Engineering, College of Engineering
[2] College of Information Sciences and Technology
Pennsylvania State University
{vkg5164, pranav.venkit, shomir, rjp49}@psu.edu

Abstract

This paper presents a comprehensive survey of work on sociodemographic bias in language models (LMs). Sociodemographic biases embedded within language models can have harmful effects when deployed in real-world settings. We systematically organize the existing literature into three main areas: types of bias, quantifying bias, and debiasing techniques. We also track the evolution of investigations of LM bias over the past decade. We identify current trends, limitations, and potential future directions in bias research. To guide future research towards more effective and reliable solutions, we present a checklist of open questions. We also recommend using interdisciplinary approaches to combine works on LM bias with an understanding of the potential harms.

1 Introduction

LMs have demonstrated impressive performance in many tasks (Raffel et al., 2020; Zhong et al., 2020; Yang et al., 2019). However, much work reveals that LMs can adopt biases present in training data (Wen et al., 2022; España-Bonet and Barrón-Cedeño, 2022; Gupta et al., 2022b; Hutchinson and Mitchell, 2019). Sociodemographic bias has been defined to occur when a model performs differently across social groups (Czarnowska et al., 2021; Chouldechova and Roth, 2020). This is concerning because when LMs are used in real-world applications, this can potentially lead to negative societal impacts (Field et al., 2023; Rudin, 2019; Blodgett et al., 2020). The urgency to understand and mitigate bias in LMs is growing. Figure 1 illustrates this trend, showing a rise in publications related to bias in natural language processing (NLP) over the past decade, sourced from SCOPUS. Our survey synthesizes results from this rapidly growing area into a roadmap for future investigations.

Other surveys on bias in NLP have thoroughly examined various aspects of bias, including bias

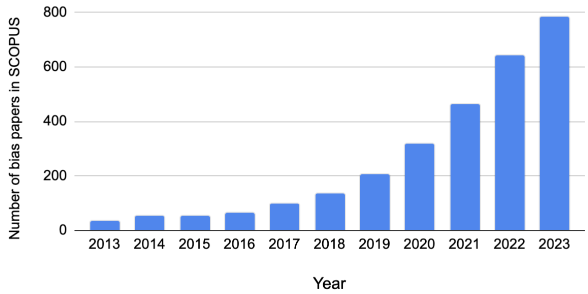

Figure 1: This graph shows number of papers/articles published each year (from 2013 to 2023) in SCOPUS that contain the term 'bias' and ('nlp' or 'language models') in the title, abstract, or keywords.

in large language models (Zhao et al., 2023) and methods for measuring bias (Czarnowska et al., 2021; Bansal, 2022), with much work on gender bias (Stanczak and Augenstein, 2021; Devinney et al., 2022). To provide a clearer picture of the diverse motivations in studies of LM bias (Blodgett et al., 2020), we present a detailed taxonomy and a timeline of bias research. Then we synthesize this work to pinpoint shortcomings and develop a checklist of open questions, to help steer future studies toward more effective and reliable methods.

In this work, we surveyed 273 papers on bias in LMs to identify current trends and limitations. We structured our survey using three perspectives: **1) a taxonomic categorization, 2) an evolutionary timeline, and 3) a roadmap for future work**. We categorized bias literature into three major strands of investigation, as shown in Fig. 2: types of bias, quantifying bias, and debiasing techniques. Then we organized our review by summarizing the findings within each category and subcategory of our taxonomy. We also identified the evolution of research into measurement and mitigation of LM bias over the past decade, as shown in Fig. 3. This perspective separates trends that had a brief life from those that continue to have promise. Finally, we offer a checklist of open questions that have continued to be challenging, or that have emerged recently, to serve as a roadmap for the future.

As a final consideration, we note there has been relatively limited exploration of interdisciplinary approaches to investigate LM bias. While LM bias measurement and mitigation is an important technical issue, we believe it is also deeply intertwined with social factors. We recommend using perspectives and methodologies from disciplines such as psychology and behavioral economics to deepen our understanding of bias. Similar to other works (Omrani et al., 2023; Mei et al., 2023), we believe that by leveraging insights across disciplines, we can develop more effective strategies for measuring and mitigating LM bias, combined with assessment of and ways to avoid social harms.

2 Understanding Bias

In this section, we highlight the critical role of interdisciplinary approaches to understand bias as a psychosocial phenomenon. These disciplines offer decades of research into human cognition and social behavior, providing valuable insights that could inform definitions of sociodemographic bias in LMs, and assessments of their potential for harm.

Recent studies have begun to integrate ideas from psychology with NLP to better understand bias (Spliethöver et al., 2022; Omrani et al., 2023; Mei et al., 2023; Omrani Sabbaghi et al., 2023), showcasing the usefulness of interdisciplinary approaches. For instance, research in psychology has long addressed the origins and expressions of social bias (Osborne et al., 2023), also proposing strategies for alleviation of bias. For example, one way to reduce bias, as found in psychology, is by engaging with individuals from diverse groups (Pettigrew and Tropp, 2006; Reimer and Sengupta, 2023). A similar idea is reflected in (Blodgett et al., 2020), which advocates for LM engineers to reduce bias through engagement with people who might be affected by applications that use LMs.

The Stereotype Content Model (SCM), a framework from social psychology, categorizes stereotypes into interpersonal and intergroup interactions, providing insights into bias dynamics (Cuddy et al., 2008). It proposes that human stereotypes are captured by two dimensions of social perception: warmth (e.g., trustworthiness, friendliness) and competence (e.g., capability, assertiveness). A recent work by (Omrani et al., 2023), for example, used the SCM framework to develop a bias mitigation method that generalize across multiple social attributes, rather than one at a time.

The Nobel Prize-winning psychologist and behavioral economist, Daniel Kahneman, discusses how mental shortcuts (biases) can be advantageous in situations requiring quick judgments (Kahneman, 2011). For example, the sentence “a large mouse climbed over a small elephant” immediately calls to mind a mouse, that while large relative to other mice, is tiny relative to the elephant, one of the largest mammals on earth. Extrapolating Kahneman’s argument to NLP, bias based on commonsense knowledge could be advantageous in enhancing an LM’s understanding of relations among real-world entities. This argue for a potential benefit of certain kinds of bias.

Kahneman (2011) defines bias as “the tendency to make systematic errors in judgment or decisions based on factors that are irrelevant or immaterial to the task at hand” and cautions that human judgment is susceptible to bias from irrelevant factors. Applying this insight to NLP, we need to understand the potential negative impact LM bias might have in real-world settings. Crawford (2017) and Barocas et al. (2017) examine *representational harm* and *alloted harm* in NLP. Representational harm arises when an NLP system represents some social groups in a less favorable light than others. Allotted harm arises when a system allocates resources or opportunities unfairly to a social group (Shahbazi et al., 2023).

In conclusion, ideas from psychology and behavioral economics provide a more informed understanding of bias. While some biases may contribute positively to model performance, others can have detrimental societal effects. An interdisciplinary approach would not only enrich our theoretical understanding of bias but could also guide the development of more effective methods to identify bias inherent in LMs, and lessen social harm.

3 Categories of Work on Bias in LMs

We used two strategies to identify candidate papers for our survey: 1) using the keywords "bias" and "fairness," we searched for papers in the ACL Anthology, NeurIPS proceedings, FAccT, and AIES conferences; 2) we included papers from citation graphs for retrieved papers. We surveyed papers released before January 1, 2024 and included them only if they addressed language modeling, thus omitting papers on speech, where different issues arise. These criteria narrowed down an initial large set of 308 papers to 273.

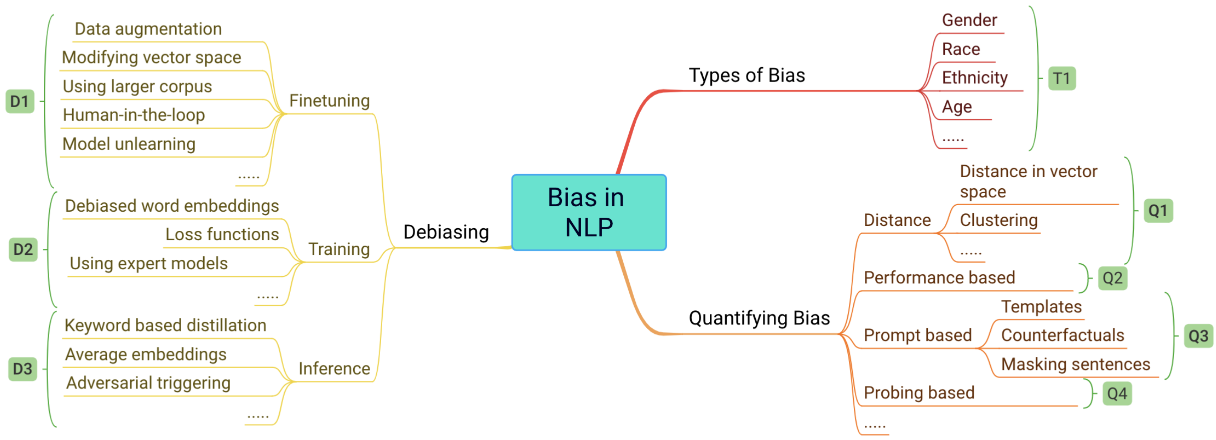

Figure 2: Three broad categories of bias research, and the upper hierarchy of each category (T, Q, D).

We categorized the literature into three key areas: (1) types of bias, (2) quantifying bias, and (3) debiasing techniques. Figure 2 illustrates our taxonomy. Subsequent sections will delve into this taxonomy in detail, with a full compilation of papers available in Appendix.

3.1 Types of Bias - *T1*

In the realm of NLP, sociodemographic bias is particularly concerning as it can lead to differential model performance across various social groups (Smith et al., 2022). Sociodemographic bias includes gender bias, when models are biased against a particular gender (De-Arteaga et al., 2019; Park et al., 2018; Du et al., 2021; Bartl et al., 2020; Webster et al., 2021; Tan and Celis, 2019); racial bias, when models are biased against certain races (Nadeem et al., 2021; Garimella et al., 2021; Nangia et al., 2020; Tan and Celis, 2019); ethnic bias, when models are partial towards certain ethnicity (Ahn and Oh, 2021; Garg et al., 2018; Li et al., 2020; Abid et al., 2021; Manzini et al., 2019; Narayanan Venkit et al., 2023); age bias (Nangia et al., 2020; Diaz et al., 2018), sexual-orientation bias (Nangia et al., 2020; Cao and Daumé III, 2020) and many others as outlined in Table 1

Sociodemographic bias can emerge from language patterns that imply assumptions about demographic differences (Lauscher et al., 2020). These biases are often ingrained in the cultural or societal nuances of training data. For example, LMs can perpetuate biases by associating certain lexical items more strongly with particular social groups. Beyond the influence of training data, (Zhou et al., 2023b) found that the size of the model, its training objectives, and tokenization strategies are important factors that affect the social bias in LMs.

Types of Bias	No. of papers	Percentage
Gender	114	48%
Race	36	15%
Ethnicity	24	10%
Nationality	18	7%
Sexual Orientation	12	5%
Ableism	11	5%
Age	9	4%
Political	6	2%
Physical Appearance	5	2%
Socioeconomic status	4	2%

Table 1: Distribution of papers on bias shows a predominant focus on gender bias.

Our review indicates a disproportionate concentration on gender bias: it is the subject of nearly half of the surveyed papers, as Table 1 illustrates. Moreover, we observed that bias evaluation and mitigation efforts are often specific to certain biases and may not generalize well.

3.2 Quantifying Bias

Measurement of bias is challenging because it is often hidden within complex LMs. However, quantifying bias is a precondition to addressing or mitigating bias that might be harmful. Here we review different methods of measuring bias in LMs and how they differ from each other. We present an overview of evaluation datasets in the appendix.

3.2.1 Distance-based metrics - *Q1*

Distance in vector space. Early efforts to quantify bias in NLP (from 2013-2019, as seen in Figure 3) primarily utilized distance metrics within embedding spaces. These approaches define certain words as 'target words' (like professions 'engineer' and 'nurse'), along with certain words as 'attributes' (often related to social categories like 'male' and 'female'). The aim was to measure the conceptual distance between these targets and attributes. The pioneering work is the Word Embedding Association Test (WEAT) score (Caliskan et al., 2017).

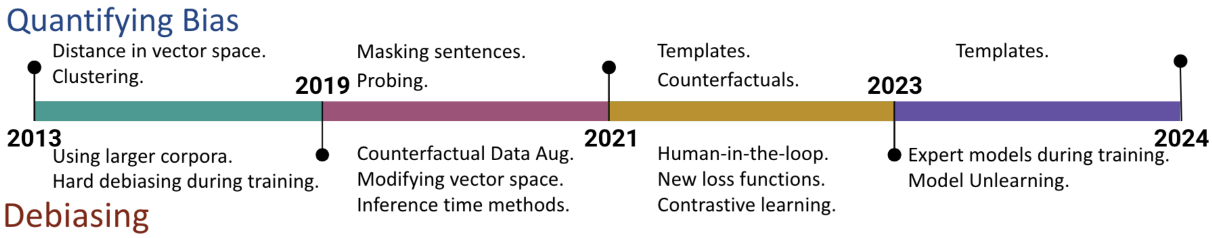

Figure 3: Evolution of changes in methods to quantify LM bias and debias LMs over the past decade.

They calculate bias as the differential association of target words with attribute sets based on cosine similarity. Subsequent to WEAT, (Dev and Phillips, 2019) proposed the Embedding Coherence Test (ECT), which simplifies an attribute category, like 'female', into a single vector by averaging the embeddings of related attribute words such as 'she', 'women', and 'girl'. Ethayarajh et al. (2019) introduced RIPA, they used the inner product instead of cosine similarity to account for vector magnitude and directionality in measuring bias.

Some works expanded WEAT to contextual embeddings (Guo and Caliskan, 2021; Tan and Celis, 2019) and sentence level embeddings (May et al., 2019). Other metrics use clustering of word embeddings (Chaloner and Maldonado, 2019). Bordia and Bowman (2019) quantified bias based on co-occurrence of words. They hypothesized that words occurring in close proximity to a particular gender in the training data are prone to be more biased towards that gender during testing.

In recent years, there are fewer approaches in *Q1*, as they require accessing a model's internal layers to quantify bias. The growing trend of larger model sizes complicates identifying the right layer for bias assessment, and the limited open-source availability of LMs raises further obstacles.

3.2.2 Performance-based metrics - *Q2*

These approaches examine how well models perform across different sociodemographic groups. They typically divides the test dataset into different groups to assess performance disparities. De-Arteaga et al. (2019) measured gender bias by comparing the true positive rates for classification involving male versus female names and pronouns. Dixon et al. (2018) and Zhao et al. (2018a) took similar approaches, using area under the curve and false positive rate (Dixon et al., 2018), and relative accuracy (Zhao et al., 2018a). Zhang et al. (2022) and Huang et al. (2020) generated augmented datasets to measure bias as the difference in accuracy between the original and augmented datasets. Stanovsky et al. (2019) proposed a metric based on differences in accuracy across genders for machine translation. Approaches in *Q2* evaluate the model's final decisions and are applicable to any model, whether open-source or not, unlike *Q1*.

3.2.3 Prompt-based metrics - *Q3*

Here we review methods that prompt models using a range of prompt-generation methods.

Template-based methods. In these approaches, models are prompted through a set of pre-defined templates, or patterns, that capture specific types of bias or stereotypes. The templates contain slots that are filled through selection from a set of pre-defined demographic target terms during evaluation. For instance, a template could be "A <PERSON> is walking" where <PERSON> is systematically substituted with names associated with different demographic groups. By analyzing the differences in the model's responses to these substitutions, the presence and degree of bias can be measured.

Prabhakaran et al. (2019) generated templates for toxicity detection, and proposed metrics based on average difference, standard deviation and range of model performance for different target groups. Smith et al. (2022) proposed a metric based on 450,000 unique sentence prompts. Webster et al. (2021) defined fourteen templates to determine gender identity bias. Felkner et al. (2023) created a dataset of 45,540 sentences using 11 templates for measuring anti-LGBTQ+ bias in LMs. Gupta et al. (2023) focused on creating 224 diverse set of templates across three NLP tasks. Parrish et al. (2022a) measured nine types of demographic bias on question answering datasets. They generated more than 25 different templates for each bias category. In contrast to performance-based metrics which divide the dataset into two parts as discussed in *Q2*, these approaches increase the size of the bias-testing dataset significantly and therefore perform a more exhaustive examination of bias.

Counterfactual-based methods. Several works aim to make template-based approaches more rigorous by examining how changing irrelevant attributes, known as protected attributes, affects model predictions. Specifically, "a decision is fair towards an individual if it is the same in (a) the actual world and (b) a counterfactual world where the individual belongs to a different social group."

Counterfactual methods alter these protected attributes in test examples to identify attributes that significantly affect model decisions (Garg et al., 2019; Kusner et al., 2017). Huang et al. (2020) created counterfactuals for a testing dataset and found that that generative LLMs like GPT-2 (Radford et al., 2019) tend to generate continuations with more positive sentiment for "baker", and more negative sentiment for"accountant" as the occupation. Gardner et al. (2020) created contrast sets by generating counterfactuals for ten NLP datasets and showed that model performance drops significantly on counterfactuals. Liang et al. (2022) substituted terms linked to specific demographic groups in the test set, examining the impact on model accuracy.

Masking Sentences. Another approach to bias measurement is to mask certain words in sentences, then analyze the model's predictions for these blanks to assess bias. Kurita et al. (2019) used this technique with occupation-related sentences, like "[MASK] is a programmer," comparing the probabilities given to male and female pronouns to identify gender biases in job associations. Similarly, Ahn and Oh (2021) quantified bias as the variance of normalized probabilities across various demographic groups. Bartl et al. (2020) used models' predictions of masked tokens to measure bias.

In recent years, template-based approaches have gained traction (Smith et al., 2022; Parrish et al., 2022b; Li et al., 2020) as seen in Figure 3. The advantage of *Q3* is their ability to reflect potential real-world impacts of bias by focusing on model outputs rather than solely analyzing internal parameters as in *Q1*. Like *Q2*, they apply broadly to both open-source and proprietary models of any size.

3.2.4 Probing metrics - *Q4*

This category evaluates bias by examining how LMs process information, often by adding a classification layer or employing probes to test the inner workings of LMs. Mendelson and Belinkov (2021) used a classifier trained on LMs latent spaces to detect biases like negative word associations and ability to detect shared lexical items from sentence representations alone. Dev et al. (2020) probed model bias using natural language inference datasets by measuring whether swapping lexical items for different sociodemographic groups changes entailment relations between sentence pairs. Li et al. (2020) examined bias in question-answering models by altering the subjects of questions and analyzing the variance in response probabilities.

These approaches face limitations like those discussed in *Q1*, as they need access to model internal layers. Moreover, the complexity and size of modern LMs introduce considerable computational and practical challenges to implementing these probing strategies effectively.

3.3 Debiasing

Debiasing methods aim to make models more fair and accurate in their predictions and recommendations (Subramanian et al., 2021). Turning to Daniel Kahneman again, he argues that reducing social stereotyping and bias has costs, but that the costs are worthwhile to achieve a better society (Kahneman, 2011). Extending the same principle to NLP, the effort and cost required for reducing biases are essential for creating fair NLP systems.

3.3.1 Debiasing during Finetuning - *D1*

These debiasing methods are applied during the finetuning phase of pre-trained LMs.

Data augmentation. Zmigrod et al. (2019) and Lu et al. (2020) introduced Counterfactual Data Augmentation (CDA), to reduce gender bias by generating counterfactual instances to balance gender representation. This involves substituting gender-specific words, such as *he* and *she* to construct novel sentences. Maudslay et al. (2019) enhanced this approach with Counterfactual Data Substitution (CDS), which assigns probabilities to these changes, aiming for more realistic modifications. Building upon these insights, (Park et al., 2018; Liang et al., 2020; Lauscher et al., 2021; Panda et al., 2022) proposed various swapping mechanisms to re-balance data distributions. Some of these data augmentation approaches are also being adapted for use during model training.

Modifying vector space. Dev et al. (2020, 2021) proposed a subspace correction and rectification method for modifying embedding space to mitigate bias. They aimed to disentangle associations between concepts that are bias-prone. Ravfogel et al. (2020) learned a linear projection over representations after training, to remove the bias components in embeddings. Manzini et al. (2019); Yifei et al.

(2023) used principal component analysis to identify and address the bias in embedding spaces. Gaci et al. (2022) redistributed attention scores to assign equal weight for words related to bias.

Fine-tuning with large corpora. Park et al. (2018) demonstrated that debiasing models benefit from fine-tuning with extensive datasets, avoiding the pitfalls of small, biased datasets. Ahn and Oh (2021) proposed that training BERT (Devlin et al., 2019) on multiple languages helps to reduce ethnic biases in each language.

Human-in-the-loop. These methods involve humans identifying biases in models, which are then used to finetuned them. Chopra et al. (2020) used human-in-the-loop methods to find words linking a sociodemographic group to a positive or negative trait. Yao et al. (2021) used human-provided explanations to find spurious bias patterns in model output, and used it to reduce bias in models.

Model Unlearning Recently, there has been more focus on model unlearning methods (cf. Figure 3). Here the main idea is to identify and alter specific model weights responsible for bias. Meissner et al. (2022) identified a subset of model weights responsible for bias and masked them during testing. The advantage of their approach is it does not require finetuning. Agarwal et al. (2023) addressed biases by adjusting weights with data augmentation, then finetuning for specific tasks with those weights fixed to prevent relearning biases. Kumar et al. (2023) captured bias mitigation functionalities using "adapters" attached to transformer blocks. Use of adapters offers a unique advantage in that they can be added to the model for bias correction in a plug-and-play fashion.

Works in *D1* offer greater ease of implementation, with customizable solutions for each model. However, as the prevalence of large language models grows, they are being trained on enormous amounts of data. In such cases, bias becomes more difficult to mitigate after models have been trained.

3.3.2 Debiasing during Training - *D2*

Several works have applied debiasing at training time or to word embeddings used at initialization.

Debiased word embeddings Bolukbasi et al. (2016) proposed a hard debiasing technique aimed at reducing gender bias in embeddings by adjusting the vector deviations between gendered and gender-neutral terms, offering these adjusted embeddings as an alternative to standard Word2Vec embeddings. Park et al. (2018); Zhao et al. (2018b) further illustrate the effectiveness of debiased embeddings in reducing gender bias in LMs.

Loss function Several methods employ specialized loss functions to minimize bias during model training. Garimella et al. (2021) used declustering loss to reduce bias. Bordia and Bowman (2019) proposed a loss regularization method. Huang et al. (2020) proposed a three-step curriculum training using distance between the embeddings as a fairness loss to reduce sentiment bias. Liu et al. (2021) and He et al. (2022a) used adversarial training and contrastive loss respectively to reduce bias in LMs. Li et al. (2023) shows that using contrastive learning during training helps in debiasing.

Expert Models for Bias Reduction Recently methods using an auxiliary model, or so-called expert model, to reduce bias have gained prominence (cf. Figure 3). Orgad and Belinkov (2023) predicted biased samples using an auxiliary model and performed sample reweighting to downweight these sample during training. Jeon et al. (2023) used binary classifiers, referred to as bias experts, to identify biased examples within a specific class. Zhang et al. (2023) used gradient-based explanations to focus on sensitive attributes and downstream tasks, adjusting the training process to balance fairness and performance effectively.

3.3.3 Debiasing at Inference Time- *D3*

These methods apply debiasing methods at test time. In general, these methods are quite diverse. Abid et al. (2021) and Venkit et al. (2023b) applied adversarial machine learning to trigger positive associations in text generative models to reduce anti-Muslim bias and nationality bias, respectively, through prompt modifications. Qian et al. (2021) performed keyword-based distillation to remove bias during inference, and to block bias acquired during training. Zhao et al. (2019) addressed gender bias through averaging of representations for different gender vocabulary. Majumder et al. (2023) used humans to provide feedback to balance between task performance and bias mitigation.

Work on debiasing during inference time faces the same issues as those in *D1*. They are easy to implement but act as a proxy to debias the models and do not completely remove the model bias.

4 Limitations of current approaches

The works surveyed here offer valuable insights towards understanding bias in LMs, and demonstrate many innovative approaches and methodologies that have advanced the field. Alongside the commendable progress, however, a thorough analysis of the body of work on bias reveals limitations which we outline in this section.

Reliability issues with bias metrics. The robustness of existing bias metrics is questionable. Metrics introduced in *Q1* and *Q2* change significantly, given minor changes in datasets or evaluation settings (Antoniak and Mimno, 2021; Spliethöver et al., 2022; Du et al., 2021; Valentini et al., 2022). Similarly, template-based methods are highly sensitive to small modifications to words used in the templates (Selvam et al., 2023; Seshadri et al., 2022; Alnegheimish et al., 2022).

Use of identical templates across bias categories. Most of the work using template-based approaches (An et al., 2023; Smith et al., 2022) use the same templates to assess diverse social biases, without considering whether certain template features should be specific to distinct types of bias. This approach risks conflating bias scores across categories, suggesting a need for more tailored templates to measure specific social biases accurately. Alternatively, investigation of ways to generalize across templates to a more abstract approach, as in (Omrani Sabbaghi et al., 2023), holds promise.

Limited Scope of Template-Based Bias Measurement. Template-based methods often use a restricted range of templates and target words, often focusing only on US-based names. This narrows their scope. Additionally, these approaches suffer from author bias, as templates are manually designed by the authors. This author bias makes their bias scores heavily dependent on template selection (Seshadri et al., 2022; Pikuliak et al., 2023).

Finetuning approaches for debiasing are not very effective. The majority of recent works on debiasing in LM focus on finetuning, valued mainly for its simplicity and adaptability. However, its effectiveness is often questionable (DiCiccio et al., 2023). The complexity and size of modern large language models, which require extensive data, time, and resources to train, makes it particularly challenging to eliminate bias through finetuning-based approaches.

Debiasing is sometimes superficial. Finetuning-based debiasing methods treat symptoms rather than root causes of bias, adjusting model outputs to appear less biased without actually removing bias from models (Gonen and Goldberg, 2019; Tokpo et al., 2023). Remarkably, some debiasing techniques can potentially increase bias (Mendelson and Belinkov, 2021). The absence of reliable bias metrics complicates the evaluation of the effectiveness of debiasing methods. We recommend that future works utilize a variety of metrics to thoroughly assess debiasing results.

Overemphasis on gender bias. As shown in Table 1, around half of the works focuses solely on gender bias. Although gender bias is a significant concern, other types of sociodemographic bias also deserve attention. Expanding research to cover a wider range of bias categories could provide a more comprehensive understanding of bias.

Lack of Sociotechnical Understanding of Bias. In the field of NLP, we have seen very little effort to understand the sociotechnical impacts of bias (Venkit et al., 2023a). Similarly, there is a lack of proper understanding of bias (Blodgett et al., 2020). A deeper exploration of bias through interdisciplinary collaborations could offer more nuanced insights and improved methodologies to measure, mitigate, prevent and assess harms from bias, as highlighted in Section 2.

Gap in Translating Bias Metrics to Real-World Impacts. There is a notable disconnect between bias metrics and their implications for real-world applications, underscoring the need for metrics that better reflect practical outcomes. It has been found that bias metrics in *Q1* do not correlate well with real-world biases (Goldfarb-Tarrant et al., 2021).

Lack of Explicit Analysis of How Models Can Cause Social Harm. Works on NLP bias often overlook the complexity of how LM bias can impact society (Dev et al., 2022). It is crucial to differentiate when biases might have positive or negative effects and to explore exactly how LM bias can lead to societal harm. A deeper exploration into the nature and consequences of LM bias is needed to fully grasp the implications, and guide efforts to diminish or prevent social harm.

Comparison of different approaches is difficult. Due to the different target domains of various approaches, it is often difficult to directly compare different approaches. Kaneko et al. (2023) compared different bias evaluation approaches without requiring the expense of human labels. We need more work in the direction of reliable and cost-effective comparison among different measurement and mitigation methods.

5 Checklist

By analyzing the strengths and limitations of current works, we have created a 14-question checklist to guide the development of future work on bias in NLP. This tool is designed to help researchers build more effective and reliable strategies. Questions 1-6 are specific to bias measurement, 7-8 address bias mitigation, and 9-14 apply to all works on LM bias. We do not intend any one work to address all questions; rather, we believe work that addresses multiple questions will have a significant impact.

[Q1] *Robustness:* Is your bias measurement stable against small modifications to templates/descriptors?

[Q2] *Country-focused data:* Does your method rely on country-specific data, such as the U.S.? If so, how can it be adapted to other countries?

[Q3] *Real-World Relevance:* How do your bias measurements reflect real-world biases, and affect end-users?

[Q4] *Future Usability:* Have you taken measures to make sure your approach is easily extendable to ensure that it is useable after 5 years?

[Q5] *Data Diversity:* Have you used diverse data sources to diminish biases present in the data sources?

[Q6] *Verification of Bias Type*: What measures have you taken to ensure your bias measurement on a given type of bias doesn't overlap or confuse with other biases?

[Q7] *Scalability and Efficiency:* Can your debiasing method efficiently scale to large models and datasets while maintaining effectiveness?

[Q8] *Monitoring and Evaluation:* Is there a way for you to continuously assess and adjust the effectiveness of your approach?

[Q9] *Extensibility to other Social Groups:* Can your method be extended to additional sociodemographic groups?

[Q10] *Risk of Misinterpretation:* Can there be a situation when your approach falsely indicates reduced bias in models?

[Q11] *Cultural Sensitivity:* Does your approach take into account the contextual and cultural variations in language use?

[Q12] *Interdisciplinary Insights:* Does your method integrate knowledge from multiple disciplines to understand bias?

[Q13] *Transparency and Reproducibility:* Is your method clear and can others can reproduce your results?

[Q14] *Community Engagement:* Does your method allow for user and community feedback?

6 Future Direction

Looking ahead, we anticipate greater emphasis on bias mitigation during LM training. Post-training bias mitigation adds to the costliness of very large LMs, and serves as a filter rather than a corrective. We have already seen progress in the direction of training time methods since we started our survey (Jeon et al., 2023). Further, contrastive learning during training has shown promising results for reducing bias (Li et al., 2023), and we expect more research in this and similar directions.

Despite their growing popularity, template-based methods for measuring bias face challenges (Selvam et al., 2023; Seshadri et al., 2022). We believe that these challenges can be tackled with careful consideration of the limitations, such as lack of robustness, leading to more effective and reliable bias measurement. We anticipate that prompt-based methods will gain prominence. Additionally, integrating interdisciplinary insights with algorithmic analysis will likely gain traction for quantifying and mitigating bias.

We believe that as robust methodologies emerge, there will be an increased emphasis on understanding and addressing intersectional bias, the overlap of multiple biases, in LMs moving forward.

7 Conclusion

We have presented a comprehensive literature survey encompassing 273 relevant works on sociodemographic bias in NLP. Our proposed categorization of the literature provides enhanced clarity regarding the current research landscape. Our survey also points towards the most promising directions for future research. We introduced a 14-question checklist designed to guide future research towards developing more effective and reliable approaches, and to avoid the pitfalls identified in previous studies. We encourage using an interdisciplinary approach to better capture and address the nuanced nature of bias in NLP systems.

8 Limitations

In our survey, we focused on works from ACL Anthology, NeurIPS proceedings, FAccT and AIES. We might have missed some relevant works in our survey, that appeared in other venues. While we have systematically organized the bias literature into categories as shown in Figure 2, which came from an extensive survey of current literature, our framework might not encompass all existing or future research. Additionally, our emphasis on sociodemographic bias means that valuable insights from works addressing other forms of bias in language models were not covered in our analysis.

9 Ethics Statement

Our work addresses the ethical impact of sociodemographic bias in NLP, offering a comprehensive survey of 273 peer-reviewed articles to highlight the presence and implications of bias within language models. By systematically organizing research findings and tracking bias approaches over the past decade, our work promotes transparency, awareness, and accountability within and beyond the NLP community. The survey provides a meticulously designed checklist, based on the weaknesses and limitations of the field, to guide future research toward more effective solutions for mitigating bias.

We also emphasize the social and ethical implications of bias underscoring the significance of addressing these issues to prevent potential negative consequences. We hope that our analysis aid in shaping more inclusive and equitable NLP technologies by fostering dialogue, awareness, and proactive measures to address sociodemographic bias, incorporating ideas beyond the field of NLP.

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A Appendix

A.1 Evaluation Datasets

Bias benchmark datasets provide valuable resources for NLP fairness research. These datasets commonly contain illustrative examples of biased language, often templated sentences filled with contrastive social group terms. Datasets allow standardized bias evaluation on diverse tasks using controlled examples. Many of them focus on a particular type of language context, such as coreference, sentiment, or question answering, while others probe for stereotype bias through word associations. Table present in the *Appendix* summarizes these datasets.

In the case of *coreference resolution*, Zhao et al. (2018a) proposed a method for identifying gender bias using Winograd-schema sentences for occupation terms. Webster et al. (2018) introduced GAP, a gender-balanced, labeled corpus of 8,908 ambiguous pronoun–name pairs designed to detect gender bias in coreference resolution. In the *word association* domain, Nangia et al. (2020) presented CrowS-Pairs, a sentence pair corpus that measures a model's bias by assessing if it favors sentences with stereotypes. Nadeem et al. (2021) released StereoSet, a large-scale natural dataset in English designed to measure stereotypical bias using inter- and intra-sentence association of words to stereotypical contexts. Li et al. (2020) proposed UNQOVER, a general framework for probing bias in *question answering* models using questions to probe whether a model associates a sociodemographic group to a stereotype. Smith et al. (2022) published HolisticBias, consisting of 450,000 unique sentence prompts for measuring 13 types of sociodemographic bias in generative LMs.

In the domain of *sentiment evaluation*, Kiritchenko and Mohammad (2018) released EEC, an 8,640 English sentence collection curated to test bias toward certain races and genders in sentiment analysis models. BITS (Venkit and Wilson, 2021; Venkit et al., 2023c) is a similar corpus of 1,126 sentences curated to measure disability, race, and gender bias in sentiment and toxicity analysis models.

Table 2 provides list of datasets for quantifying bias in NLP models.

A.2 List of papers surveyed

Below is the list of papers surveyed in this work, sorted based on our taxonomy.

Explicit Bias(T1) :

(Mei et al., 2023; Deas et al., 2023; Liu et al., 2021; De-Arteaga et al., 2019; Bell and Sagun, 2023; Silva et al., 2021; Park et al., 2018; Sap et al., 2020; B et al., 2021; Lauscher and Glavaš, 2019; Rozado, 2020; Rudinger et al., 2017; Shah et al., 2020; Du et al., 2022; Nozza et al., 2022; Honnavalli et al., 2022; Lucy and Bamman, 2021; Mendelson and Belinkov, 2021; Matthews et al., 2021; Cao et al., 2022; Papakyriakopoulos et al., 2020; Kementchedjhieva et al., 2021; Garrido-Muñoz et al., 2021; Strengers et al., 2020; Delobelle et al., 2022; Fisher et al., 2020; Sheng et al., 2020; Zhang et al., 2020a; Hendricks et al., 2018; Mehrabi et al., 2021; Mayfield et al., 2019; Schwartz et al., 2021; Nozza et al., 2019; Vaidya et al., 2020; He et al., 2019; Hovy and Søgaard, 2015; Wolfe and Caliskan, 2021; Sakaguchi et al., 2021; Agarwal et al., 2019; White and Cotterell, 2021; Luo and Glass, 2023)

Gender Bias : (Sharma et al., 2022; Kaneko et al., 2022a; Stahl et al., 2022; Kaneko et al., 2023; Toro Isaza et al., 2023; Hada et al., 2023; Attanasio et al., 2023; Goldfarb-Tarrant et al., 2023; Lee et al., 2023; Gaut et al., 2020; Sun et al., 2019; Hamidi et al., 2018; Zhou et al., 2019; Savoldi et al., 2021; Sahlgren and Olsson, 2019; Ahn et al., 2022; Tal et al., 2022; Kaneko et al., 2022b; Field and Tsvetkov, 2020; Garimella et al., 2019; Escudé Font and Costa-jussà, 2019; Bhaskaran and Bhallamudi, 2019; McCurdy and Serbetci, 2020; Kaneko and Bollegala, 2019; Larson, 2017; Du et al., 2021; Bartl et al., 2020; Webster et al., 2021; Tan and Celis, 2019; Bolukbasi et al., 2016; Maudslay et al., 2019; Zhao et al., 2019; Rudinger et al., 2018; Lu et al., 2020)

Racial Bias : (Goldfarb-Tarrant et al., 2023; Levy et al., 2023; Field et al., 2023; Cheng et al., 2023; Sap et al., 2019; Hanna et al., 2020; Blodgett et al., 2016; Davidson et al., 2019; Friedman et al., 2019; Shen et al., 2018; Karve et al., 2019; Nadeem et al., 2021; Garimella et al., 2021; Nangia et al., 2020; Tan and Celis, 2019; Guo and Caliskan, 2021; Brown et al., 2020)

Disability bias : (Venkit and Wilson, 2021; Venkit et al., 2022; Hutchinson et al., 2020; Bennett and Keyes, 2020; Mills and Whittaker, 2019; Hassan et al., 2021; Narayanan Venkit, 2023)

Ethnicity bias : (Bauer et al., 2023; Levy et al., 2023; Malik et al., 2022; Li et al., 2022; Ahn and Oh, 2021; Garg et al., 2018; Li et al., 2020; Abid et al., 2021; Manzini et al., 2019; Venkit et al., 2023b; Bhatt et al., 2022), Nationality bias - (Ladhak et al., 2023; Levy et al., 2023; Narayanan Venkit et al., 2023), Political bias - (Thebault-Spieker et al., 2023; Shen et al., 2018; Rozado, 2020), Age bias (Nangia et al., 2020; Diaz et al., 2018) and sexual-orientation bias (Ovalle et al., 2023; Nangia et al., 2020; Cao and Daumé III, 2020)

Distance based metrics(Q1) : (Caliskan et al., 2017; Dev and Phillips, 2019; Zhao et al., 2017; Basta et al., 2019; Shen et al., 2018; Brunet et al., 2019; May et al., 2019; Dev et al., 2021; Zhou et al., 2019; Pujari et al., 2020; Sutton et al., 2018;

Dataset name	Task	Bias Type	Dataset Size
WinoBias (Zhao et al., 2018a)	Coreference Resolution	Gender	1,580
WinoGender (Rudinger et al., 2018)	Coreference Resolution	Gender	720
GAP (Webster et al., 2018)	Coreference Resolution	Gender	8,908
Counter-GAP (Xie et al., 2023)	Coreference Resolution	Gender	4,008
CrowS-Pairs (Nangia et al., 2020)	Word Association	Gender, race, religion, age, sexual orientation, nationality, disability, physical appearance, and socioeco. status.	1,508
StereoSet (Nadeem et al., 2021)	Word Association	Race, gender, religion, and profession	16,995
WikiGenderBias (Gaut et al., 2020)	Word Association	Gender	45,000
UnQOVER (Li et al., 2020)	Word Association	Gender, Nationality, Ethnicity,Religion	8,908
WinoGrande (Sakaguchi et al., 2021)	Word Association	Dataset Bias	1,767
BBQ (Parrish et al., 2022b)	Word Association	9 Sociodemographic Group	58,492
EEC (Kiritchenko and Mohammad, 2018)	Sentiment Evaluation	Gender, Race	8,640
BITS (Venkit and Wilson, 2021)	Sentiment Evaluation	Gender, Race, Disability	1,126
HolisticBias (Smith et al., 2022)	Text Generation	13 Sociodemographic Group	450,000

Table 2: List of Evaluation datasets used to measure bias in NLP models

Lauscher et al., 2020; Guo and Caliskan, 2021; Bolukbasi et al., 2016; Ross et al., 2021; Tan and Celis, 2019; Ethayarajh et al., 2019; Chaloner and Maldonado, 2019; Bordia and Bowman, 2019; Valentini et al., 2023)

Performance metrics(Q2) : (De-Arteaga et al., 2019; Kwon and Mihindukulasooriya, 2022; Zhang et al., 2022; Huang et al., 2020; Dixon et al., 2018; Zhao et al., 2018a; Cho et al., 2019; Stanovsky et al., 2019; Gonen and Webster, 2020; Borkan et al., 2019; Dev et al., 2020)

Prompt based metrics(Q3) : (Nagireddy et al., 2023; Webster et al., 2021; Smith et al., 2022; Kurita et al., 2019; Krishna et al., 2022; Bhaskaran and Bhallamudi, 2019; Gupta et al., 2022b; Prabhakaran et al., 2019; Ahn and Oh, 2021; Bartl et al., 2020; Li et al., 2020; Venkit and Wilson, 2021; Salazar et al., 2020; Dev et al., 2020; Diaz et al., 2018; Zhang et al., 2020b; Garg et al., 2019; Liang et al., 2022; Kusner et al., 2017; Huang et al., 2020; Akyürek et al., 2022; Gardner et al., 2020; Ousidhoum et al., 2021; Parrish et al., 2022a; Kiritchenko and Mohammad, 2018; Touileb et al., 2023; Gupta et al., 2023; Pikuliak et al., 2023; Touileb et al., 2023; An et al., 2023; Felkner et al., 2023)

Probing based metrics(Q4) : (Ousidhoum et al., 2021; Dev et al., 2020; de Vassimon Manela et al., 2021; Immer et al., 2022; Kennedy et al., 2020; Sweeney and Najafian, 2019; Tan et al., 2020; Li et al., 2020; Mendelson and Belinkov, 2021)

Debiasing during Finetuning(D1) : (Ungless et al., 2022; Du et al., 2023; Omrani et al., 2023; Zhou et al., 2023a; Thakur et al., 2023; Jin et al., 2021; He et al., 2022b; Zmigrod et al., 2019; Jin et al., 2021; Gaci et al., 2022; Gupta et al., 2022a; Ghaddar et al., 2021; Kumar et al., 2020; Han et al., 2021; Attanasio et al., 2022; Joniak and Aizawa, 2022; Chopra et al., 2020; Maudslay et al., 2019; Park et al., 2018; Yao et al., 2021; Liang et al., 2020; Sen et al., 2022; Ma et al., 2020; Limisiewicz and Mareček, 2022; Yang et al., 2021; Wang et al., 2021; Pujari et al., 2020; Sedoc and Ungar, 2019; Tan et al., 2020; Sutton et al., 2018; Ravfogel et al., 2020; Kaneko and Bollegala, 2019; Karve et al., 2019; Gyamfi et al., 2020; Shin et al., 2020; Zhang et al., 2020a; Wen et al., 2022; Chopra et al., 2020; Yang and Feng, 2020; Lu et al., 2020; Lauscher et al., 2021; Garg et al., 2019; Dev et al., 2020, 2021; Manzini et al., 2019; Bolukbasi et al., 2016; Ahn and Oh, 2021; Orgad et al., 2022; Felkner et al., 2023)

Debiasing during Training (D2) : (An et al., 2022; Bolukbasi et al., 2016; He et al., 2019; Han et al., 2022; Liu et al., 2020b; Escudé Font and Costa-jussà, 2019; Prost et al., 2019; James and Alvarez-Melis, 2019; Park et al., 2018; Zhao et al., 2018b; Gao et al., 2022; Sweeney and Najafian, 2020; Hube et al., 2020; Sen and Ganguly, 2020; Saunders and Byrne, 2020; Dixon et al., 2018; Karimi Mahabadi et al., 2020; He et al., 2022a; Richardson et al., 2023) Loss functions for bias mitigation : (Hashimoto et al., 2018; Qian et al., 2019; Berg et al., 2022; Romanov et al., 2019; Garimella et al., 2021; Bordia and Bowman, 2019; Huang et al., 2020; Provilkov and Malinin, 2021; Liu et al., 2021; Orgad and Belinkov, 2023; Li et al., 2023)

Debiasing during Inference (D3) : (Majumder et al., 2023; Qian et al., 2021; Zhao et al., 2019; Abid et al., 2021; Guo et al., 2022; Schick et al., 2021; Venkit et al., 2023b)

Works on Bias : These are works that are difficult to categorize in one of the above categories. (Chouldechova and Roth, 2020; Green, 2019; Zhang and Bareinboim, 2018; Mayfield et al., 2019; Katell et al., 2020; Dwork et al., 2012; Jacobs et al., 2020; Anoop et al., 2022; Czarnowska et al., 2021; Blodgett et al., 2021; Zhuo et al., 2023; Mulligan et al., 2019; Jacobs and Wallach, 2021; Schoch et al., 2020; Franklin et al., 2022; Bender, 2019; España-Bonet and Barrón-Cedeño, 2022; Hutchinson and Mitchell, 2019; Bender et al., 2021; Goldfarb-Tarrant et al., 2021; Brown et al., 2020; Li et al., 2020; Bagdasaryan et al., 2019; Liu et al., 2020a; Zhiltsova et al., 2019; Chopra et al., 2020; Luo et al., 2023; Shah et al., 2020; Garrido-Muñoz et al., 2021; Delobelle et al., 2022; Czarnowska et al., 2021)