Fairness in NLP with Graph-based Representations: A Systematic Survey

Anonymous ACL submission

Abstract

As widespread use of large language models (LLMs) grows, concerns about their bias and fairness have become central ethical issues. As social bias is highly context-dependent, understanding not only text but the relational structures beyond the text is crucial. Graph-based representations capture structural relationships within and across texts and have recently been integrated with LLMs to address fairness with promising results. However, there is to date no comprehensive review of joint uses of graphs and LLMs for fairness. To address this gap, we systematically analyze graph-based approaches to fairness and their integration with LLMs, and outline key future research directions.

1 Introduction

Large Language Models (LLMs) have driven remarkable advancements in Natural Language Processing (NLP), demonstrating strong capabilities in generating human-like text and performing diverse tasks even without training (Li et al., 2024a; Liu et al., 2024). Despite their widespread adoption across fields, LLMs face persistent challenges in reliability, transparency, and trustworthiness, particularly due to harmful or biased outputs arising from systematic social biases in training data and algorithms (Mehrabi et al., 2021; Gupta et al., 2024).

Social bias in text is often implicit and highly context-dependent, making it challenging to detect and mitigate (Gallegos et al., 2024). The perceived bias in text may vary depending on the speaker, target audience, or situational context, even when the sentence conveys the same literal meaning. For example, the statement *"Those people are always late."* can be a casual complaint about colleagues, but it becomes a harmful stereotype when directed at a racial or national group. This highlights that bias often arises from relational structures between entities rather than isolated lexical tokens, leaving LLMs particularly vulnerable when processing unstructured text (Deshpande et al., 2022).

Graphs represent structural relationships, enabling flexible applications across domains (Zhong et al., 2023; Li et al., 2024b) and offering several advantages for addressing fairness challenges. Graphs can enhance explainability, allowing researchers to trace how LLMs generate biased reasoning (Xie et al., 2025; Wasi, 2024). Graphs also provide contextual understanding beyond sentence boundaries by capturing both local and global structural information (Baez Santamaria et al., 2024; Panayotov et al., 2022; Lei and Huang, 2024). In addition, graphs allow LLMs to leverage external knowledge without domain-specific retraining (Zhao et al., 2025). As a result, research on fairness using graph-based representations has grown recently (as summarized in table 3 of appendix A).

While prior surveys have examined the integration of graphs and LLMs (Li et al., 2024b; Jiang et al., 2025; Pan et al., 2024), none have systematically analyzed how graph representations and their integration with LLMs contribute to fairness. To the best of our knowledge, this work presents the first comprehensive survey of graph-based approaches for fairness. We organize this survey around three research questions:

RQ1. In what ways can structured representations enhance fairness in language models?

RQ2. How can they be integrated with language models to identify or mitigate social bias?

RQ3. What are the key opportunities and challenges in graph-LLM integration for fairness?

2 Bias and Fairness

A variety of definitions of fairness, bias types, tasks (including mitigation methods), and evaluations have been proposed.

Definitions Fairness is a social and ethical principle that in machine learning and NLP typically de-

Bias Type	Example
Demographic	It was a very important discovery, one you wouldn't expect from a **female** astrophysicist.
Identity-based	How is all that awesome **Muslim** diversity going for you native Germans? You have allowed this yourselves. If you do not stand and fight against this. You get what you asked for, what you deserve!
Ideological	**Right**: Top Texas Republicans resist gun control and push for more armed teachers and police at schools in wake of Uvalde shooting. **vs** **Left**: Calls grow for gun control after Texas school shooting: 'Our kinds are living in fear'.
Cultural	Q: I'm traveling to Japan. **How do I thank for services to fit in?** A: Show gratitude with a tip.

Table 1: Examples of bias types. The demographic bias from Nangia et al. (2020) illustrates how a seemingly complimentary statement can reflect gender bias. The identity-based bias from Wasi (2024) shows implicit toxicity toward Muslims. The ideological bias from Liu et al. (2023a) reveals biased framing based on political leaning. The cultural bias example from Shi et al. (2024) demonstrates culturally unaware LLM responses.

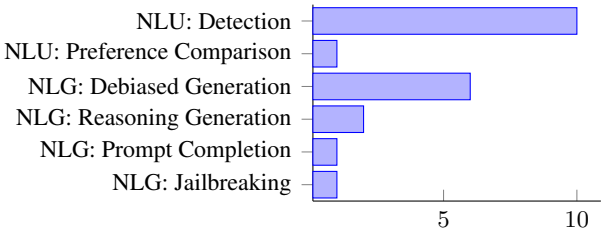

Figure 1: Distribution of graph-based fairness research across task types.

notes the absence of bias or discrimination in model predictions and representations (Ferrara, 2023; Li et al., 2024a). It should be an intentional and deliberate goal (Ferrara, 2023) and may be operationalized through statistical criteria such as equalized odds (Mehrabi et al., 2021). Many definitions of fairness have been studied. Group fairness, examining disparities in model outcomes across demographic groups, has often been the center of efforts in bias mitigation in NLP (Deshpande et al., 2022; Wasi, 2024; Ma et al., 2024; Zhao et al., 2025). Individual fairness, ensuring that similar individuals receive similar outcomes, has been argued to be a better, more fine-grained notion of fairness (Chen et al., 2025). Counterfactual fairness, grounded in causal modeling, requires that predictions remain invariant under counterfactual changes to protected attributes such as gender or race (Kusner et al., 2017; Xie et al., 2025; Jin et al., 2025). Informational fairness, reducing ideological bias and promoting narrative neutrality, has also been studied (Liu et al., 2023a; Lei and Huang, 2024, 2025).

Bias Types Bias types can be categorized according to the social groups or attributes they target. Examples of these types are illustrated in Table 1.

Fairness studies often address broad demographic and identity-based biases, including gender, nationality, and race (Ghosh et al., 2023; Ma et al., 2024; Zhao et al., 2025; Xie et al., 2025; Luo et al., 2025; Chen et al., 2025; Jin et al., 2025). Many rely on established benchmark datasets such as CrowS-pairs (Nangia et al., 2020) and StereoSet (Nadeem et al., 2021), though some construct task-specific datasets via prompting (Xie et al., 2025; Ma et al., 2024). Other works narrow the focus to specific identity-based biases, such as ethnicity (Deshpande et al., 2022) or religion (Wasi, 2024).

Fairness studies have also analyzed ideological bias at multiple granularities, including sentence, article, topic, and media levels (Lei and Huang, 2025; Manzoor et al., 2025; Lei and Huang, 2024; Liu et al., 2023a; Panayotov et al., 2022; Liu et al., 2023b). Ideological bias is often expressed implicitly through context and framing without explicit lexical cues, and thus requires reference to structured representations of the broader discourse context and relational structure.

Bias Tasks Natural language understanding (NLU) tasks determine the meaning of text by generating a label from a predefined output space. Examples include bias detection where classification is between biased vs. unbiased, and preference comparison where probabilities between biased and counterfactual counterparts are compared (Bölücü and Canbay, 2021; Panayotov et al., 2022; Liu et al., 2023b; Ghosh et al., 2023; Lei and Huang, 2024; Wasi, 2024; Ma et al., 2024; Manzoor et al., 2025; Zhao et al., 2025; Jin et al., 2025). Natural language generation (NLG) tasks generate open-ended textual outputs rather than selecting from a predefined output space. Examples include debiased text generation, reasoning generation (Xie et al., 2025), prompt completion (Salinas et al., 2024), and jailbreaking (Luo et al., 2025). Figure 1 shows the distribution of research across tasks.

The NLG tasks of debiasing can be further subcategorized into *Pre-processing* and *In-processing*, based on where the intervention takes place in the model development pipeline (Mehrabi et al., 2021; Gallegos et al., 2024; Liu et al., 2024). *Pre-processing* debiasing methods are applied before model training, targeting inputs such as constructing structured data or counterfactual knowledge

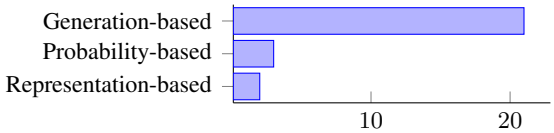

Figure 2: Distribution of graph-based fairness research across evaluation metric types.

(Deshpande et al., 2022; Liu et al., 2023a; Chen et al., 2025). For example, structured data is built with cultural knowledge and used to fine-tune models (Deshpande et al., 2022). *In-processing* interventions directly modify model architecture or training procedures through techniques such as adding encoders, updating parameters, and equalizing loss functions (Liu et al., 2023a; Ma et al., 2024; Baez Santamaria et al., 2024; Lei and Huang, 2025; Preciado Márquez et al., 2025; Chen et al., 2025). For example, Chen et al. (2025) introduces a mitigation objective that minimizes the probability gap between predictions on biased inputs and their counterfactual knowledge.

Bias Evaluations Common datasets used for bias evaluation (table 4 of appendix A) are mainly evaluated by generation/prediction, probability, or representation (Gallegos et al., 2024; Gupta et al., 2024; Liu et al., 2024). Figure 2 shows the distribution of research across these evaluation types.

Generation/prediction-based metrics are the most common, and evaluate extrinsic bias in the outputs of downstream tasks. They typically rely on standard evaluation measures from downstream tasks such as classification and summarization (Bölücü and Canbay, 2021; Deshpande et al., 2022; Panayotov et al., 2022; Liu et al., 2023b; Ghosh et al., 2023; Wasi, 2024; Baez Santamaria et al., 2024; Lei and Huang, 2024; Zhao et al., 2025; Preciado Márquez et al., 2025; Xie et al., 2025; Lei and Huang, 2025; Jin et al., 2025). Some studies define task-specific evaluation functions or apply external classifiers to outputs (Ma et al., 2024; Luo et al., 2025; Baez Santamaria et al., 2024; Salinas et al., 2024; Chen et al., 2025). For example, Luo et al. (2025) define a more successful attack as one with a higher bias rate and a lower refusal rate:

$$\text{Refusal Rate} = \frac{1}{N}\sum_{i=1}^{N} \mathbf{I}[\,K(R_i) = 1\,]$$

where N is the number of inputs, and $K(R_i) = 1$ if any predefined refusal keyword is found in response R_i or 0 otherwise.

Several works evaluate the generated text with lexicon-based valence-arousal-dominance metrics (Lei and Huang, 2025; Liu et al., 2023a). For example, Lei and Huang (2025) follow Lee et al. (2022) in computing Arousal$^+$, Arousal$^-$, and Arousal$_{sum}$ = Arousal$^+$ + Arousal$^-$, defined as:

$$\text{Arousal}^+ = \sum_{\substack{w \in A_{\text{neu}} \\ v(w) > 0.65}} a(w) \quad \text{Arousal}^- = \sum_{\substack{w \in A_{\text{neu}} \\ v(w) < 0.35}} a(w)$$

where w is a word from the generated neutral summary A_{neu}, $v(w)$ its valence from a lexicon list w, and $a(w)$ its arousal score.

Probability-based metrics evaluate bias by measuring the models' internal preference (assigned probabilities) for one phrasing over another. For example, Ma et al. (2024); Chen et al. (2025); Jin et al. (2025) use the CrowS-Pairs score (Nangia et al., 2020), defined as the percentage of examples for which a model assigns a higher likelihood to the stereotyping sentence than the non-stereotyping sentence in the paired CrowS-Pairs data.

Finally, representation-based metrics measure the bias based on the embedding-level disparity or similarity between texts (Salinas et al., 2024; Baez Santamaria et al., 2024). For example, Salinas et al. (2024) examines representation diversity by analyzing the distribution of embeddings associated with protected group entities.

3 Graph Representations

A graph is a pair $G = (N, E)$, where N is a set of nodes and E is a set of edges $(n_1, n_2) \in N \times N$. What nodes and edges are used to represent varies by purpose. Graphs are often coupled with graph neural networks to encode nodes and edges into low-dimensional spaces (Cao et al., 2024).

Graph Structures Many studies decompose text into (*entity, relation, entity*) triplets in subject-predicate-object or event-relation-event forms (Luo et al., 2025; Ma et al., 2024; Liu et al., 2023a; Deshpande et al., 2022; Salinas et al., 2024; Liu et al., 2023b; Chen et al., 2025; Jin et al., 2025), such as *"(white lives matter, is against, black lives matter)"* (Zhao et al., 2025). These triplets may form local text-level graphs or be linked across texts to build document or corpus-level graphs with entities as nodes and relations as edges. Some event-centric graphs are enriched with temporal, causal, and coreference relations (Liu et al., 2023b; Lei and Huang, 2024; Liu et al., 2023a; Lei and Huang, 2025). For example, Lei and Huang (2025) integrates temporal information into graphs to analyze news data, and Xie et al. (2025) incorporates causal

relations to show reasoning over biased questions.

Contextual graphs represent entire utterances or dialogues as nodes, modeling discourse-level relations for social bias, which often emerges in context rather than isolated sentences. In hate-speech detection and counterspeech generation, edges capture conversational context such as authorship, similarity, mention, or adjacency (Bölücü and Canbay, 2021; Ghosh et al., 2023; Wasi, 2024; Baez Santamaria et al., 2024; Preciado Márquez et al., 2025).

Graphs are also used to model networks among entities, such as media outlets, for media bias analysis (Manzoor et al., 2025; Panayotov et al., 2022).

Graph Extraction and Completion Table 5 in appendix A summarizes data sources commonly used for graph construction and reasoning. Graph construction often involves named entity recognition, coreference resolution, and relation extraction, implemented with rule-based extraction, fine-tuning LLMs, or LLM-based generation.

Rule-based methods rely on predefined relations in datasets (Ma et al., 2024; Manzoor et al., 2025; Panayotov et al., 2022; Ghosh et al., 2023) or information extraction systems (Deshpande et al., 2022; Baez Santamaria et al., 2024; Preciado Márquez et al., 2025; Liu et al., 2023a). For example, Ma et al. (2024) extracts entities from WordNet (Miller, 1992) and corresponding 'is-a' hypernyms from ConceptNet (Liu and Singh, 2004) as high-level semantic categories. Information extraction systems such as Stanford OpenIE (Angeli et al., 2015) extract triplets from text via syntactic parses.

Graph construction through fine-tuning involves training LLMs on event or relation extraction datasets for inference (Lei and Huang, 2024, 2025; Liu et al., 2023a,b). For example, Liu et al. (2023b) fine-tunes an event extraction model on the MATRES data (Ning et al., 2018) for temporal relation learning for ideology prediction.

Graphs can be directly constructed by LLMs through embedding-based or prompt-based generation (Salinas et al., 2024; Wasi, 2024; Zhao et al., 2025; Luo et al., 2025; Chen et al., 2025; Xie et al., 2025; Jin et al., 2025). These approaches can infer missing nodes or edges, or expand graphs by generating new triplets from partial inputs, enabling flexible and scalable graph construction.

Graph Neural Networks (GNNs) GNNs learn node, edge, or graph-level embeddings via message passing and neighborhood aggregation (Li et al., 2024b). Gaph convolutional networks (GCN; Kipf and Welling, 2017) aggregate feature information from local neighbors in each convolution layer, with stacked layers capturing larger neighborhoods. Graph attention networks (GAT; Veličković et al., 2018) compute node hidden states through attention weights over neighboring nodes. GraphSAGE networks (Hamilton et al., 2017) generate embeddings by sampling and aggregating features from a node's local neighborhoods, enabling inductive learning on unseen nodes (Zhou et al., 2020).

4 LLMs + Graphs + Fairness

Having established a preliminary understanding of social bias and graph representations separately, we turn to the intersection of these topics, focusing on how to integrate graph representations with LLMs. Table 3 in appendix A summarizes this literature.

4.1 Roles of Graph Representation

We categorize the roles of graphs in fairness studies based on their components and extraction sources. Figure 3 illustrates three types: structure analysis, external knowledge, and contextual representation.

Structure Analysis In structure analysis, illustrated in figure 3(a), graphs analyze or formalize relationships between structured semantic units within an utterance, decomposing them into triplets such as *(subject, predicate, object)* or *(event, relation, event)* (Salinas et al., 2024; Liu et al., 2023b,a; Ma et al., 2024; Lei and Huang, 2024, 2025; Xie et al., 2025; Chen et al., 2025; Jin et al., 2025). For example, Lei and Huang (2024) constructs an event relation graph for sentence-bias identification in news articles, where events are reported occurrences or actions, and coreference, temporal, causal, and subevent relations connect these events. This makes the implicit relations explicit, enabling comparison of embedded biases across articles and revealing underlying framing bias within text. As another example, Xie et al. (2025) constructs a causal graph not from the input text, but from an LLM-generated reasoning, and then analyzes the graph to study the LLM's internal bias.

External/Additional Knowledge Graphs in this role, illustrated in figure 3(b), complement LLM internal knowledge by providing domain-specific and supplementary knowledge to LLMs in the form of graphs constructed from datasets distinct from the model's input (Luo et al., 2025; Zhao et al., 2025; Manzoor et al., 2025; Deshpande et al., 2022; Panayotov et al., 2022; Ma et al., 2024). Exter-

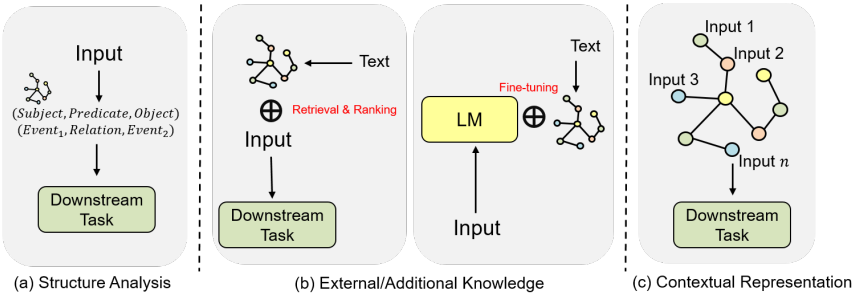

Figure 3: Roles of graphs in fairness research. Graphs are used for (a) structure analysis of inputs, (b) external knowledge from additional data, and (c) discourse-level contextual modeling.

nal knowledge may be inserted at inference time through input augmentation, where for example Zhao et al. (2025) enables fine-grained judgments about hatred and toxicity by querying a meta-toxic knowledge graph, retrieving relevant information, and using that to augment the input text. Alternatively, external knowledge can be inserted at training time through fine-tuning on a domain-specific dataset to expand and recalibrate the LLM's internal knowledge (Deshpande et al., 2022).

Contextual Representation Graphs in this role, illustrated in figure 3(c), assist in understanding biased expressions that are situational rather than self-contained, by capturing relationships across multiple utterances, documents, or discourse segments (Bölücü and Canbay, 2021; Ghosh et al., 2023; Liu et al., 2023a; Wasi, 2024; Baez Santamaria et al., 2024; Lei and Huang, 2025; Preciado Márquez et al., 2025). Such assistance is needed, as the meaning of hate speech and counterspeech often emerges from the dialogue or conversational history (Preciado Márquez et al., 2025; Wasi, 2024; Baez Santamaria et al., 2024; Bölücü and Canbay, 2021; Ghosh et al., 2023). For example, Wasi (2024) constructs a graph where nodes represent speech and edges reflect cosine similarity between node embeddings, and applies a graph encoder to derive explanations that illustrate why a speech targeting Islam is hateful based on relational cues and discourse patterns.

4.2 Graph-LLM Integration Frameworks

We categorize graph-LLM integration frameworks based on interactions between graph representations and bias-identifying or mitigating LLMs. Figure 4 illustrates the types: graph-retrieval-augmented LLM, LLM-driven graph, graph-enhanced LLM, graph-analyzed LLM, and graph-LLM fusion. The frameworks are not mutually exclusive; studies may apply hybrid approaches.

Graph-Retrieval-Augmented LLM. In this integration, illustrated in figure 4(a), an external knowledge graph is queried and the LLM input is augmented with relevant subgraphs that provide additional information about potential biases (Luo et al., 2025; Zhao et al., 2025). For instance, Luo et al. (2025) adversarially attacks a language model by retrieving the top k triplets most similar to the original query and adding them to the input prompt, eliciting harmful responses. Similarly, Zhao et al. (2025) maps toxic knowledge to entities extracted from text based on semantic similarity, filters irrelevant knowledge, then inserts the selected knowledge into the prompt to enhance toxicity detection. Graph retrieval augmentation can be cost efficient as no retraining of the LLM is required to apply it to new domains. However, it relies heavily on the quality and completeness of the retrieved graph.

LLM-Driven Graph. In this integration, illustrated in figure 4(b), LLMs generate entities and relations directly from natural language text to provide richer structures supporting fairness analysis (Luo et al., 2025; Liu et al., 2023a; Lei and Huang, 2025, 2024; Liu et al., 2023b; Jin et al., 2025). LLMs may be prompted to produce graph representations like triplets using the LLMs' internal knowledge, or may be fine-tuned on datasets containing events and relations to expand the LLMs' ability to produce graph representations.

A common way to construct graphs is to prompt LLMs to generate triplets from input text (Luo et al., 2025; Liu et al., 2023a; Zhao et al., 2025; Jin et al., 2025). For example, Luo et al. (2025) uses few-shot examples to LLMs, Zhao et al. (2025) provides textual rationales to assist an LLM in extracting toxic triplets, and Liu et al. (2023a) first uses an LLM to generate summaries and then uses an LLM to constructs graphs from the summaries. However, prompting LLMs for graph construction could have risks: if biases are embedded in LLMs,

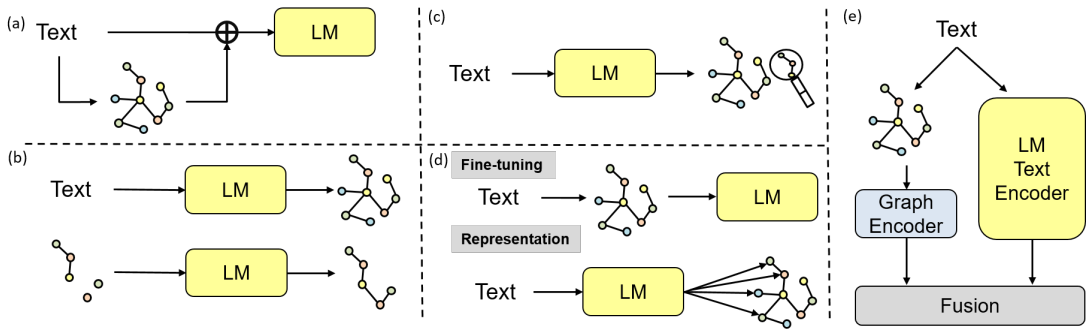

Figure 4: Integration frameworks of graphs and LLMs in fairness research: (a) graph-RAG LLM, (b) LLM-driven graphs, (c) graph-analyzed LLM, (d) graph-enhanced LLM, and (e) graph-LLM fusion.

hallucinated and inaccurate graphs could be generated and propagated into downstream analyses.

When fine-tuning LLMs to construct graphs, studies typically employ datasets for event identification or relation extractors (Lei and Huang, 2025, 2024; Liu et al., 2023b). For example, Lei and Huang (2025) train an event trigger word identifier along with relation extractors that predict coreference, temporal, causal, and subevent relations given an event pair. However, fine-tuning on datasets for graph construction could have risks if when biases exist in the datasets (Stranisci et al., 2024). Evaluation has typically relied on measuring alignment with human-annotated relations and, occasionally, additional human validation, but never explicitly examined whether biases in LLM outputs are embedded into the graph structures.

Graph-Enhanced LLM. In this integration, illustrated in figure 4(d), parameters or representations of LLMs are updated or enriched using graph structures (Ma et al., 2024; Bölücü and Canbay, 2021; Wasi, 2024; Liu et al., 2023b; Chen et al., 2025). This integration focuses on incorporating graphs into a model, either via fine-tuning or via representation enhancement.

In graph-enhanced LLM fine-tuning, structured representations are used to recalibrate LLMs' internal biases by fine-tuning models on less biased or counterfactual graphs, or by incorporating bias-aware loss functions (Deshpande et al., 2022; Ma et al., 2024; Liu et al., 2023b; Chen et al., 2025). For example, Ma et al. (2024) construct a graph based on word hypernyms such as "a CEO is an employee" and continue LLM pre-training on this hypernym information, reducing biased associations with "CEO" by incorporating the broader concept of "employee". Chen et al. (2025) reduce probability gaps between a biased triplet (*s1,r1,o1*) and its counterfactual knowledge (*s2,r2,o2*) through a gap-based loss integrated into the training objectives.

In representation enhancement, graph structures enrich LLM representations by providing explicit contextual information and modeling structured relationships among entities (Bölücü and Canbay, 2021; Wasi, 2024). For example, Wasi (2024) construct a graph where nodes represent content embeddings and edges represent contextual similarity between two nodes, then apply a GNN to better capture the subtleties of hate speech.

While the graph-enhanced LLM framework is able to reliably recalibrate or update LLM representations, it requires retraining for each new domain.

Graph-Analyzed LLM. In this integration, illustrated in figure 4(c), graphs are used to analyze LLMs' internal knowledge or reasoning process by prompting them to generate or complete graph representations (Xie et al., 2025; Chen et al., 2025; Salinas et al., 2024). For example, Xie et al. (2025) prompts LLMs to generate both answers and causal graphs representing their reasoning, identifying biased causal reasoning in LLMs when answering questions with sensitive attributes (e.g., gender, race, nationality). Other studies evaluate the bias embedded in LLMs by prompting them to complete graph structures, generating corresponding objects when given subjects and predicates (Chen et al., 2025; Salinas et al., 2024). Salinas et al. (2024) analyzes generated objects across gender and ethnicity dimensions, while Chen et al. (2025) compares prediction probabilities for associated objects between socially biased subjects and their counterfactual counterparts. The graph-analyzed LLM framework is well-suited for diagnostic studies prioritizing interpretability, with graph-based outputs serving as a lens to interpret and quantify the LLMs' internal social biases.

Graph-LLM Fusion. In this integration, illustrated in figure 4(e), models first separately pro-

Work	Score	Dataset	Metric	Task	Integration Framework
Lei and Huang (2025)	1.26/0.71	Neus	Arousal ↓	Debiased Generation	Fusion, LLM-Driven
Liu et al. (2023a)	6.12/3.60	Neus	Arousal ↓	Debiased Generation	LLM-Driven
Zhao et al. (2025)	72.38	HateXplain	F1-score ↑	Bias Detection	Graph-RAG, LLM-Driven
Wasi (2024)	74.7	HateXplain	F1-score ↑	Reasoning Generation, Bias Detection	Graph-Enhanced
Lei and Huang (2024)	52.00	BASIL	F1-score ↑	Bias Detection	Fusion, LLM-Driven
Liu et al. (2023b)	68.50	BASIL	F1-score ↑	Bias Detection	LLM-Driven, Graph-Enhanced
Ghosh et al. (2023)	64.65	IHC	F1-score ↑	Bias Detection	Fusion
Zhao et al. (2025)	69.95	IHC	F1-score ↑	Bias Detection	Graph-RAG, LLM-Driven
Chen et al. (2025)	49.7/51.3	CrowsPairs	CrowSPairs Score	Preference Comparison	Graph-Enhanced, Graph-Analyzed
Ma et al. (2024)	48.1/49.2	CrowsPairs	CrowSPairs Score	Debiased Generation, Bias Detection	Graph-Enhanced
Chen et al. (2025)	51.2/51.9	StereoSet	StereoSet Score	Preference Comparison	Graph-Enhanced, Graph-Analyzed
Ma et al. (2024)	58.7/55.0	StereoSet	StereoSet Score	Debiased Generation, Bias Detection	Graph-Enhanced

Table 2: Studies using the same datasets and evaluation metrics. Better performance is indicated by lower arousal scores (↓), higher F1 scores (↑), and scores closer to 50 for Crows-Pairs and StereoSet. Arousal is reported separately for $\text{Arousal}^{+}/\text{Arousal}^{-}$, CrowS-Pairs Score and StereoSet Scores are reported separately for Gender/Race.

cess texts and graphs then fuse the two representations to allow both modalities to contribute to downstream reasoning (Ghosh et al., 2023; Lei and Huang, 2024, 2025; Baez Santamaria et al., 2024; Preciado Márquez et al., 2025; Panayotov et al., 2022; Manzoor et al., 2025). The fusion between two modalities can occur at an early or late stage.

In early fusion, the graph encoder and text encoder outputs are coordinated through a mapping objective or projected into a shared semantic space (Ghosh et al., 2023; Lei and Huang, 2024, 2025; Baez Santamaria et al., 2024; Preciado Márquez et al., 2025). For instance, Lei and Huang (2025) generate neutralized summaries by constructing a graph from ideologically diverse articles, encoding graph structure through a GNN and a textualized graph through an LLM, then fusing the two representations within a shared self-attention layer.

In late fusion, the graph and text encoder outputs are combined at the final stage without projecting them into a shared space or modifying the internal LLM architecture (Manzoor et al., 2025; Panayotov et al., 2022). For example, Manzoor et al. (2025) obtains a final label distribution by concatenating label distributions predicted by a GNN over the with those generated by an LLM over the text.

Because graph-LLM fusion keeps separate streams for graph and text—unlike graph-enhanced LLMs where graphs change the internal representations of text—they may be more stable for training and more easily integrated with models that are too large to be fully fine-tuned.

4.3 Systematic Comparisons

Different graph-based integrations for fairness are rarely evaluated on overlapping datasets, metrics, and tasks. Table 2 lists all studies to date that share datasets. Graph-retrieval-augmented LLMs are evaluated on HateXplain (Mathew et al., 2021) and IHC (ElSherief et al., 2021), but are compared against only a single work. Graph-LLM fusion is evaluated on NeUS (Lee et al., 2022), BASIL (Fan et al., 2019), and IHC (ElSherief et al., 2021), yet across different tasks. This highlights the need for standardized evaluation protocols and shared datasets to enable controlled comparisons between different graph-based fairness studies.

5 Opportunities and Future Directions

Motivated by gaps in current graph-based fairness studies, and inspired by pipelines and architectures outside of fairness research where graph-LLM integration has been used to improve factual reasoning and verification (Pan et al., 2024), we outline potential opportunities and future research directions.

Assumptions in Graph-based Fairness Graph-based fairness approaches rely on several implicit assumptions that need further examination. First, many methods assume that triplets sufficiently capture the structural sources of bias, measuring induced changes to protected attributes or relations, but not accounting for confounding factors such as broader discourse structures, contextual cues, or implicit associations. Second, it is often assumed that a central perspective constitutes neutrality or less biased, despite "Center" itself being socially constructed. Third, in graph–LLM integration frameworks, graph-based representations are used for retrieval, reasoning, or analysis, implicitly assuming that these graphs can be used without introducing, propagating, or amplifying bias, yet

research on fairness in graph representation learning has shown that graph structure and message passing can propagate bias (Spinelli et al., 2022; Liu et al., 2023c). Future work is needed to explore evaluation methods that account for confounding factors, to better define and measure neutrality, and to measure fairness not only in final outputs but also across graph construction and graph learning.

Linguistic Diversity and Type-Specific Biases Most existing studies focus on English datasets. Bias mitigation strategies effective in English may not generalize to other languages because the salience and sensitivity of particular biases vary by linguistic and cultural context. Expanding fairness studies to multilingual and cross-cultural contexts is thus essential for the robustness of fairness approaches (Ramesh et al., 2023). Most studies also focus on social or ideological bias, often using broad, multi-type social bias datasets. Research is needed on underexplored bias types such as religion, disability, or age, improving representation of such biases in bias datasets, and allowing a deeper understanding of how bias manifests and can be mitigated in different contexts.

Explainability of Graphs Graph structures can enhance interpretability by enabling transparent tracing of reasoning paths. As social bias is often nuanced and context-dependent, future work should prioritize interpretable explanations or counter-speech that improve trust in models by clarifying how and why bias is detected or mitigated.

Effectiveness of Integration Strategies Though we review five types of graph-LLM integration, systematic comparisons of which integration stage is most effective for fairness (e.g., fine-tuning, input augmentation, representation learning) remain largely unexplored. Comparative analyses across integration stages are needed to identify where integrations exert the strongest effect and understand their relative and joint contributions.

Fairness-sensitive Evaluation Protocols Graph construction introduces multiple sources of uncertainty. Fine-tuning may inherit social biases from relation extraction datasets (Stranisci et al., 2024) and achieve relatively low extraction accuracy (Lei and Huang, 2024, 2025). LLMs can generate hallucinated triplets, while automatic information extraction systems produce noisy data (Deshpande et al., 2022). These challenges call for comprehensive evaluation protocols that combine intrinsic and extrinsic assessments, such as scoring-function analysis and graph-completion benchmarks, alongside human validation. Moreover, fairness mitigation should preserve factual and biologically grounded biases (e.g., breast cancer is more common in women) rather than enforcing uniform outputs across social groups (Chen et al., 2025). Evaluation frameworks should therefore include metrics that assess whether commonsense and factual knowledge are retained after debiasing, ensuring a balance between fairness and factual integrity.

LLM Agents for Fairness With the growing reasoning and decision-making capabilities of LLMs, the paradigm of *LLMs as agents* has emerged, where models dynamically plan, retrieve, and reason over information (Ren et al., 2024). However, current graph-based fairness frameworks treat graphs as fixed relational structures, even though social knowledge and bias patterns are dynamic and context-dependent. Future research on agentic LLMs for fairness may offer a way to address this limitation, enabling dynamic reasoning, verification, and revision of knowledge in graphs. LLM agents could dynamically interact with graphs used for fairness research, similar to the knowledge graph interactions of agent-based frameworks such as RoG (Luo et al., 2024) and ToG (Sun et al., 2024), including identifying inaccuracies or hallucinations in knowledge from retrieved graphs, refining or augmenting graphs dynamically during reasoning, and assessing discrepancies with counterfactual counterparts (e.g., alternative demographic attributes). LLM agents could thus encourage the consideration of multiple plausible relational pathways before generating an answer.

6 Conclusion

This survey reviews research at the intersection of fairness in NLP and graph-based representations. We first introduced the overviews of fairness and graph representations, then presented taxonomies that describe the roles of graphs – structure analysis, external knowledge, and contextual representation– and categorized graph-LLM integration frameworks. Building on identified challenges, we proposed future directions for developing fairness-specialized frameworks, more reliable evaluations, examining effective integration strategies, and agentic LLM systems. These directions highlight the potential of graph-LLM integration to advance fairness in NLP while improving the explainability and trustworthiness of LLMs.

Limitations

We acknowledge several limitations of this survey. First, we do not provide definitions or detailed methods of fairness and graphs. Instead, we offer an overview grounded in prior research and organize the reviewed literature according to defined categories, focusing on graph-LLM integration strategies for fairness rather than coverage of each area. Second, although social bias is often categorized by source, such as representation bias or algorithmic bias, we do not structure our analysis along this dimension. Nevertheless, many reviewed approaches implicitly address different bias sources through mechanisms such as architectural modification or knowledge augmentation. Third, while we outline the roles of graphs in fairness and integration categories, these are not exhaustive and may overlap with general graph-LLM frameworks. Nevertheless, we emphasize fairness-specific perspectives by highlighting how and why graphs contribute to bias detection and mitigation. Finally, the majority of the reviewed literature focuses on English language datasets, which may limit the generalizability, and some recent works may have been omitted. As ethical concerns surrounding LLMs continue to grow, future surveys can build upon and extend this work.

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A Appendix

Work	Task	Role	Integration
Bölücü and Canbay (2021)	Bias Detection	Context	Graph-Enhanced
Deshpande et al. (2022)	Knolwedge Detection	External	Graph-Enhanced
Panayotov et al. (2022)	Bias Detection	External	Fusion
Liu et al. (2023a)	Debiased Generation	Structure	LLM-Driven
Liu et al. (2023b)	Bias Detection	Structure	LLM-Driven, Graph-Enhanced
Salinas et al. (2024)	Prompt Generation	Structure	Graph-Analyzed
Ghosh et al. (2023)	Bias Detection	Context	Fusion
Ma et al. (2024)	Debiased Generation, Bias Detection	Structure	Graph-Enhanced
Lei and Huang (2024)	Bias Detection	Structure	Fusion, LLM-Driven
Baez Santamaria et al. (2024)	Debiased Generation	Context	Fusion
Wasi (2024)	Reasoning Generation, Bias Detection	Context	Graph-Enhanced
Lei and Huang (2025)	Debiased Generation	Structure	Fusion, LLM-Driven
Manzoor et al. (2025)	Bias Detection	External	Fusion
Xie et al. (2025)	Reasoning Generation	Structure	Graph-Analyzed
Zhao et al. (2025)	Bias Detection	External	Graph-RAG, LLM-Driven
Luo et al. (2025)	Jailbreaking	External	Graph-RAG, LLM-Driven
Preciado Márquez et al. (2025)	Debiased Generation	Context	Fusion
Chen et al. (2025)	Preference Comparison	Structure	Graph-Enhanced, Graph-Analyzed
Jin et al. (2025)	Bias Detection	Structure	LLM-Driven

Table 3: A summary of fairness research that uses structure representations, categorized by task, role of graph, and integration strategy. An increasing number of such studies have emerged in recent years across diverse tasks.

Dataset	Bias Type	Source	Language
WinoBias (Zhao et al., 2018)	Demg.	Synthetic	EN
WinoGender (Rudinger et al., 2018)	Demg.	Synthetic	EN
BASIL (Fan et al., 2019)	Ideog.	News	EN
Reddit (Qian et al., 2019)	Demg., Ident.	Social media	EN
GAB (Qian et al., 2019)	Demg., Ident.	Social media	EN
BiasedSents (Lim et al., 2020)	Ideog.	News	EN
ACL-2020 (Baly et al., 2020)	Ideog.	News	EN
CrowS-Pairs (Nangia et al., 2020)	Demg., Ident.	Crowdsourced	EN
Xhate-999 (Glavaš et al., 2020)	Demg., Ident.	News, Social media, Wikipedia	EN, SQ, HR, DE, RU, TR
SBIC (Sap et al., 2020)	Demg., Ident.	Social media	EN
WikiBias (Zhong et al., 2021)	Demg., Ideog.	Wikipedia	EN
CAD (Vidgen et al., 2021)	Demg., Ident., Ideog.	Social media	EN
ToxicSpans (Pavlopoulos et al., 2021)	Demg., Ident.	Social media	EN
IHC (ElSherief et al., 2021)	Demg., Ident.	Social media	EN
StereoSet (Nadeem et al., 2021)	Demg., Ident.	Crowdsourced	EN
BOLD (Dhamala et al., 2021)	Demg., Ident., Ideog.	Wikipedia	EN
BBQ (Parrish et al., 2022)	Demg., Ident.	Synthetic	EN
HolisticBias (Smith et al., 2022)	Demg., Ident., Ideog.	Synthetic	EN
NeuS (Lee et al., 2022)	Ideog.	News	EN
BIGNEWS (Liu et al., 2022)	Ideog.	News	EN
DIALOCONAN (Bonaldi et al., 2022)	Demg., Ident.	Social media	EN
HateXplain (Mathew et al., 2021)	Demg., Ident.	Social media	EN
HASOC (Mandl et al., 2025)	Demg., Ident., Ideog.	Social media	EN, BN
ML-MTCONAN-KN (Bonaldi et al., 2025)	Demg., Ident.	Crowdsourced, News, Wikipedia	EN, EU, IT, ES
DECODINGTRUST (Wang et al., 2023)	Demg., Ident.	Synthetic	EN
BiasScope (Chen et al., 2025)	Demg., Ident.	Crowdsourced, Synthetic	EN

Table 4: A summary of datasets used in the reviewed literature and the representative datasets in fairness research. Demg.,Ident.,and Ideog. indicate demographic, identity-based, and ideological bias, respectively.

Task	Data Source
Knowledge Base	WordNet (Miller, 1992) ConceptNet (Liu and Singh, 2004) Freebase (Bollacker et al., 2008) DBpedia (Auer et al., 2007) Google Knowledge Graph[1] Wikidata (Vrandečić, 2012)
Event RE	ACE 2005 (Mitchell et al., 2005) NYT (Riedel et al., 2010) RED (O'Gorman et al., 2016) DocRED (Yao et al., 2019) MAVEN (Wang et al., 2020) MAVEN-ERE (Wang et al., 2022)
Coreference	CoNLL-2011 (Pradhan et al., 2011) CoNLL-2012 (Pradhan et al., 2012) Winograde (Sakaguchi et al., 2021) KnowRef (Emami et al., 2019)
Temporal RE	TimeBank-Dense (Chambers et al., 2014) THYME (Bethard et al., 2015, 2016, 2017) MATRES (Ning et al., 2018)
Causal RE	Causal-TB (Mirza et al., 2014) EventStoryLine (Caselli and Vossen, 2017) CausalBank (Li et al., 2020)

[1] https://developers.google.com/knowledge-graph

Table 5: Data sources commonly used for graph-construction and reasoning tasks. RE refers to relation extraction.