

# SPAR-Hate: Auditor-Guided Multi-Perspective Role Reasoning for Bilingual Hate Speech Parsing

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## Abstract

**⚠ Warning: This paper contains content that may be offensive or harmful.**

Hate speech research has moved from coarse-grained classification towards structured parsing, where systems jointly identify targets, supporting arguments, and target-level labels. Documents with multiple targets, conflicting local readings, or culturally coded language make these bindings difficult to recover. SPAR-Hate is an auditor-guided multi-perspective role-reasoning framework for bilingual hate speech parsing. It decomposes each document into local focus units, elicits evidence-grounded candidates from Victim, Moderator, and Cultural Bystander perspectives, resolves candidate conflicts under grounding and schema constraints, and reassembles sample-level predictions. Experiments on STATE-ToxicCN and a controlled TBO split show gains across local and API backbones, concentrated on strict joint target–argument–label metrics. Full-test integrated-prompt controls, component ablations, and bounded-arbitration diagnostics identify the contribution of separated perspective generation and arbitration. Structured teacher traces also support training a smaller student model.

## 1 Introduction

Hate speech detection identifies hateful expressions whose interpretation depends on context, social judgement, and platform standards (Schmidt and Wiegand, 2017; Fortuna and Nunes, 2018). Fine-grained work now includes rationale annotation, target–argument parsing, and tuple extraction (Pavlopoulos et al., 2021; Mathew et al., 2021; Zampieri et al., 2023; Bai et al., 2025). Structured hate parsing predicts one or more target-level tu-

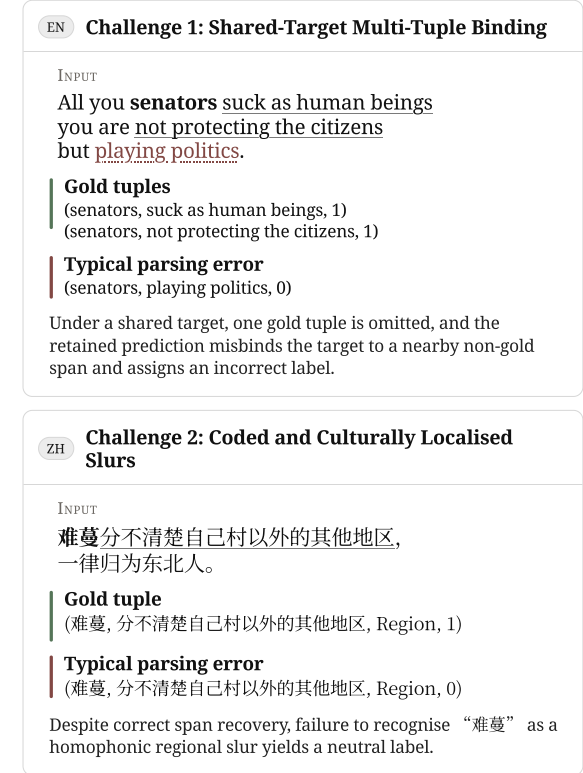


Figure 1: Typical LLM errors in bilingual hate parsing, including omitted tuples, imprecise target–argument binding, and failed interpretation of culturally localised homophonic slurs.

ples, each linking an attacked target, its supporting argument, and a target-level label.

Figure 1 shows omitted tuples, faulty target–argument binding, and a missed homophonic slur. These failures require consistent tuple prediction and culturally grounded interpretation. Large language models remain skewed towards Western cultural representations (Naous et al., 2024), weakening performance on implicit, coded, and locally grounded hate (ElSherief et al., 2021; Nozza,

2021; Ocampo et al., 2023; Lin et al., 2026). Cultural knowledge can change target identification, evidence selection, and harm attribution. Social position also shapes interpretations of hostile speech (Spears, 2021), so the same utterance can support different grounded readings.

SPAR-Hate comprises four stages: Segment, Perspective-Guided Role Generation, Arbitrate, and Reassemble. Phase 1 produces local focus units. Victim, Moderator, and Cultural Bystander generators produce evidence-grounded candidates for each unit. Phase 3 clusters and selects candidates under grounding and schema constraints, and Phase 4 restores sample-level predictions. The Chinese Cultural Bystander receives weak lexical context for coded language and local slang (Bai et al., 2025; Xiao et al., 2024; Lu et al., 2023).

Across local and API settings, SPAR-Hate improves the stricter joint structural metrics on Chinese STATE-ToxicCN and the controlled English TBO split. Component ablations test each phase, integrated-prompt controls test separated perspective generation and arbitration, and distillation transfers the structured traces to a smaller student model.

**Contributions.** The task formulation aligns Chinese and English structured parsing at field level while retaining their original annotation contracts. The framework combines local focus-unit segmentation, three perspective-conditioned generators, constrained arbitration, and sample-level reassembly. Main experiments, full-test integrated-prompt controls, ablations, and diagnostics test strict structural recovery and structured teacher-trace transfer.

## 2 Related Work

### 2.1 From Hate Speech Classification to Structured Tuple Parsing

Hate speech research began largely as text classification, but class labels alone do not support fine-grained semantic understanding. Early work focused on definitions, features, and classification models (Schmidt and Wiegand, 2017; Fortuna and Nunes, 2018; Waseem and Hovy, 2016; Davidson et al., 2017). Later multilingual shared tasks and richer annotations showed that multilingual hate analysis requires more than single-label prediction (Basile et al., 2019; Ousidhoum et al., 2019). Toxic Spans, HateXplain, TBO, and

STATE-ToxicCN then moved the field toward fine-grained localisation, rationale annotation, target-argument parsing, and Chinese quadruple parsing (Pavlopoulos et al., 2021; Mathew et al., 2021; Zampieri et al., 2023; Bai et al., 2025).

SPAR-Hate focuses on local target-argument-label bindings under separate Chinese and English annotation contracts and evaluates their sample-level reconstruction.

### 2.2 Implicit Hate, Cultural Context, and Cross-Lingual Fragility

Implicit, subtle, and context-dependent hate remains difficult to detect. Coded and indirect expressions weaken model performance (ElSherief et al., 2021; Ocampo et al., 2023; Hartvigsen et al., 2022), while HateCheck identifies related functional failures (Röttger et al., 2021). Cross-lingual zero-shot models can also misread language-specific non-hateful taboo expressions as hate signals (Nozza, 2021).

Explainable hate-speech detection uses rationales, social bias frames, and stepwise explanations (Mathew et al., 2021; Sap et al., 2020; Yang et al., 2023). Structured parsing adds the requirement that target, argument, and label remain jointly aligned. SPAR-Hate supplies cultural knowledge as weak context and retains only text-grounded candidates.

### 2.3 Role-Conditioned Reasoning and Constrained Aggregation

RoleLLM and multi-perspective role-playing show that role conditioning elicits distinct knowledge and reasoning biases (Wang et al., 2024). Proposer-aggregator methods coordinate several model outputs (Du et al., 2023). AutoGen and MetaGPT organise role allocation and structured workflow handoffs, with MetaGPT encoding these handoffs through standard operating procedures (Wu et al., 2023; Hong et al., 2024).

SPAR-Hate constrains role outputs to comparable target-argument-label candidates before aggregation. Its distillation traces retain focus-unit decomposition, role hypotheses, conflict diagnosis, and final arbitration, linking the method to chain-of-thought, self-consistency, and reasoning distillation (Wei et al., 2023; Wang et al., 2023; Shridhar et al., 2023; Hsieh et al., 2023).

### 3 Methods: The SPAR-Hate Framework

SPAR-Hate combines local focus-unit decomposition, multi-perspective candidate generation, dynamic arbitration, and sample-level reassembly in an auditor-guided framework for bilingual hate parsing. The pipeline breaks document-level parsing into explicit intermediate stages, which helps long texts, multi-target cases, implicit attacks, and culturally coded slang.

#### 3.1 Task Formulation and Output Contracts

Given an input document  $D$ , the system must predict a set of target-level structured tuples

$$E = \{e_1, e_2, \dots, e_n\}. \quad (1)$$

The Chinese and English benchmarks follow different original annotation contracts. STATE-ToxicCN uses quadruples

$$e_{zh}^{raw} = (target, argument, group, hateful), \quad (2)$$

where group denotes the attacked group category. TBO uses triples

$$e_{en}^{raw} = (target, argument, harmful). \quad (3)$$

These schemas correspond respectively to the Target–Argument–Hateful–Group annotation contract in STATE-ToxicCN and the target–argument–harmfulness contract in TBO (Bai et al., 2025; Zampieri et al., 2023).

To construct the bilingual main track at field level, the Chinese main track removes group and uses a three-field output

$$e_{zh}^{main} = (target, argument, label). \quad (4)$$

For unified notation, each tuple on the aligned bilingual main tracks is written as  $e_i = (t_i, a_i, \ell_i)$ . Here  $t_i$  denotes the attacked target,  $a_i$  the attack argument, and  $\ell_i \in \{0, 1\}$  the target-level harmfulness label. It corresponds to harmful in English and hateful in Chinese. The Chinese four-field extension retains group as an additional field.

The Chinese three-field task supports the bilingual main comparison. A four-field extension retains group and tests adaptation to the original language-specific schema. Separate prompt templates and output constraints preserve both contracts.

#### 3.2 Framework Overview

SPAR-Hate has four stages: *Segment*, *Perspective-Guided Role Generation*, *Arbitrate*, and *Reassemble*, corresponding to Phase 1–4. The system splits a document into local focus units, generates structured candidates from three perspectives, arbitrates them with a dynamic-beacon procedure, and reassembles benchmark-aligned sample-level outputs. Figure 2 presents the full pipeline.

#### 3.3 Phase 1: Local Focus-Unit Segmentation

Long texts often contain multiple targets, local stances, and interfering attack fragments. Direct extraction from the full document can therefore produce target–argument mismatches, overly wide arguments, and merged events. Divide-and-conquer frameworks for document-level sentiment parsing suggest the same advantage for structured extraction (Wang et al., 2026). Phase 1 therefore uses an LLM-based segmenter to map document  $D$  to a set of local decision units

$$G = \{g_1, g_2, \dots, g_k\}. \quad (5)$$

Each local unit  $g_i$  stores sample-level and local indices (group\_id, local\_group\_id), local text (group\_text), a focus-marked local context (focus\_text), and a soft target anchor (canonical\_target). A focus unit is defined around a target and local intent while retaining enough context for argument grounding. Its boundary need not coincide with a syntactic boundary.

#### 3.4 Phase 2: Perspective-Guided Role Generation

Perspective shapes hate judgements (Waseem and Hovy, 2016; Sap et al., 2020). The task-motivated role set covers affected-group harm, platform-governance boundaries, and community interpretation of implicit or culturally coded hate. For each local unit  $g_i$ , the framework instantiates three role-conditioned generators

$$R = \{r_{\text{victim}}, r_{\text{moderator}}, r_{\text{bystander}}\}. \quad (6)$$

Victim emphasises felt harm, exclusion, and microaggressions. Moderator emphasises platform-governance boundaries and explicit rule violations. Cultural Bystander emphasises local cultural context, community slang, pragmatic history, and coded expression. Each role generates one or more

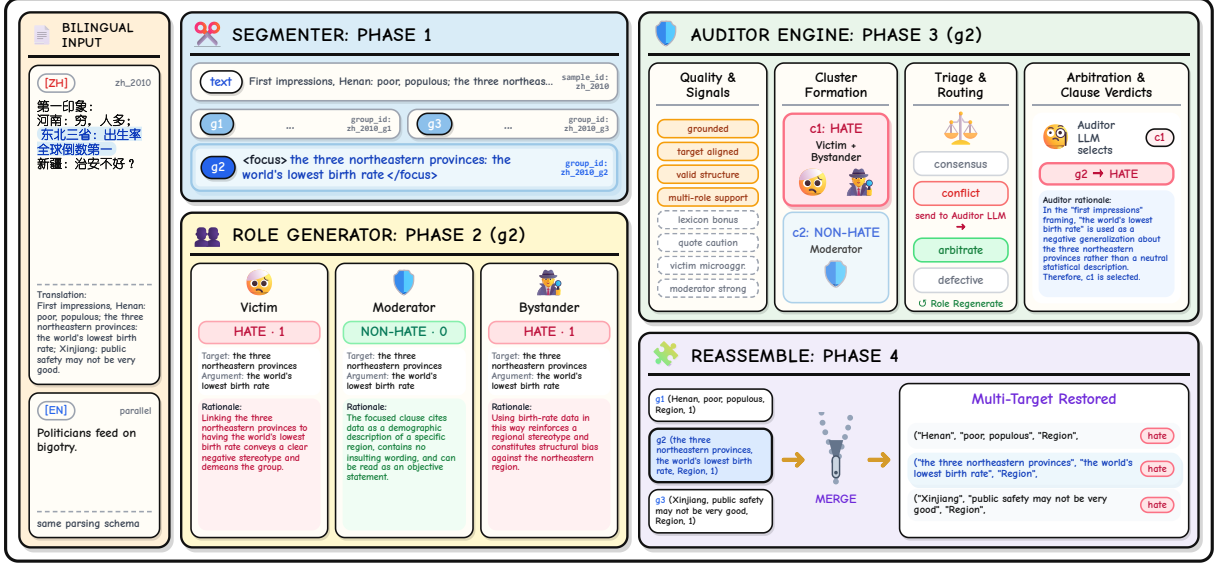


Figure 2: Overview of SPAR-Hate. Bilingual input is segmented into local focus units, processed by three role-conditioned generators, arbitrated under evidence constraints, and reassembled into sample-level outputs. Distillation uses the earlier phases to construct teacher traces for student training.

structured candidates over the same `focus_text`, yielding the role-specific candidate set

$$H_r(g_i) = \{h_r^{(1)}, h_r^{(2)}, \dots\}. \quad (7)$$

SPAR-Hate imposes a strict JSON schema and requires argument to be a supporting substring inside `focus_text`. Every judgement includes local textual evidence.

The Chinese Cultural Bystander receives entries from the auxiliary STATE-ToxicCN lexicon. Its 829 term/category/definition records contain no sample identifiers, gold tuples, or instance labels. Retrieved entries provide weak context for the current `focus_text` and `canonical_target`. Candidates remain subject to focus-span grounding, and lexicon-only singleton candidates are discarded. Lexicon hits occur in 10.1% of ZH-main groups and 9.6% of ZH-quadruple groups. Chinese toxicity research motivates this support for slang, homophones, and emoji cloaking (Lu et al., 2023; Bai et al., 2025; Xiao et al., 2024). Appendix B gives the prompt templates.

### 3.5 Phase 3: Local Candidate Clustering and Auditor Arbitration

Phase 3 filters, clusters, and ranks the role candidates for each local unit. Given

$$\mathcal{H}_i = \bigcup_{r \in R} H_r(g_i), \quad (8)$$

the procedure applies quality scoring, cluster formation, triage, and deterministic selection.

**Candidate Quality Scoring** The system first assigns each candidate  $c \in \mathcal{H}_i$  a quality score  $q(c)$ :

$$q(c) = \sum_j \alpha_j \phi_j(c). \quad (9)$$

Here  $\phi_j(c)$  includes grounding, target explicitness, consistency with `canonical_target`, structural completeness, label validity, and, in the Chinese four-field setting, group-label coherence. Chinese bystander candidates can receive a small lexicon bonus. Candidates below quality 0.60 are filtered before clustering. An ungrounded or missing argument fails validation.

**Cluster Formation** Candidates are then clustered by similarity over target, argument, harmful/hateful, and, in the Chinese four-field extension, group. Similarity between a candidate and a cluster is written as

$$\text{sim}(c, C) = \beta_t s_t(c, C) + \beta_a s_a(c, C) + \beta_y s_y(c, C) + \beta_g s_g(c, C), \quad (10)$$

where  $s_t, s_a, s_y, s_g$  denote similarity in target, argument, label, and group. On the three-field main tracks,  $\beta_g = 0$ . The reported field weights are 0.45/0.45/0.05/0.05, respectively. Each cluster is then compressed into a canonical tuple and assigned a cluster score based on member quality, the number of supporting roles, and any lexicon-

aware bonus:

$$\text{Score}(C) = \sum_{c \in C} q(c) + \lambda_1 |\text{supp}(C)| + \lambda_2 \mathbb{I}_{\text{lex}}(C), \quad (11)$$

where  $\text{supp}(C)$  is the set of roles supporting that cluster. The mainline support-role and lexicon-cluster bonuses are 0.12 and 0.08; the candidate-level lexicon bonus is 0.05.

**Triage and Dynamic Soft Beacons** After clustering, the system routes each local unit into one of three lanes according to role agreement, the margin of the top cluster, and signals of structural failure or missing roles. A clearly dominant top cluster with no obvious defect enters consensus. Missing roles or a lack of valid grounded candidates enters defective. The remaining cases enter conflict. The system then applies grounding-aware, lexicon-aware, and quote-aware soft beacons to adjust cluster ranking. If some roles are marked defective and regeneration is enabled, one bounded regeneration round is allowed. Highly conflicting cases can trigger a second auditor refinement.

### Deterministic Fallback and Local Refinement

Final ranking uses a deterministic cluster-level fallback. The selected primary cluster undergoes local refinement of target and argument boundaries. The reported configuration retains at most two clusters, requires score  $\geq 1.05$  and at least two supporting roles, and allows one regeneration round for a defective role. Across retained runs, 55.9–61.7% of focus units enter the conflict lane and 65.1–70.7% invoke auditor refinement. Appendix D reports the complete scoring, routing, and boundedness diagnostics.

### 3.6 Phase 4: Sample-Level Multi-Target Reassembly

In this task setting, local focus-unit decisions are made internally while the benchmark expects sample-level predictions. Phase 4 therefore restores earlier decisions to the output format required by evaluation. The system first aggregates all local tuples by `sample_id`, producing

$$\tilde{E}(x) = \bigcup_{g_i \in G(x)} Y(g_i), \quad (12)$$

where  $Y(g_i)$  is the set of final tuples output by Phase 3 for local unit  $g_i$ . The main configuration uses a concatenate-first strategy, preserving

local provenance and not forcing exact deduplication. The default exported sample-level prediction is therefore

$$\hat{E}(x) = \tilde{E}(x), \quad (13)$$

whereas under optional exact deduplication

$$\hat{E}(x) = \text{Dedup}(\tilde{E}(x)). \quad (14)$$

## 4 Experiments

### 4.1 Datasets and Evaluation Protocol

**Datasets** Experiments are conducted on Chinese STATE-ToxicCN and English TBO (Bai et al., 2025; Zampieri et al., 2023). STATE-ToxicCN keeps its official train/test split. The public release of TBO provides only a test split, so the public test set is deterministically shuffled with seed=20260415 and re-divided into 3200/800 train/test subsets. Beyond this repartition, processing is limited to field cleaning, schema normalisation, and split freezing. No extra relabelling is introduced, and multi-target documents are not split at this stage. The paper reports three evaluation tracks, ZH-main, EN-main, and ZH-quadruple, all defined exactly as in Section 3.1. Dataset composition appears in Table 1. TBO numbers are controlled within-paper comparisons on this deterministic split only; they are not directly comparable to studies evaluated on the original public test-only release.

**Evaluation metrics** The original evaluation protocols of both benchmarks are kept. No mixed cross-lingual total score is constructed. For Chinese, following STATE-ToxicCN, both Hard and Soft Macro-F1 are reported: Hard requires exact agreement with gold spans and field combinations, while Soft credits overlapping spans under the same target-centred structure (Bai et al., 2025).

| Dataset       | Public Split        | Final Split | Tracks                |
|---------------|---------------------|-------------|-----------------------|
| STATE-ToxicCN | official train/test | 6424 / 1605 | ZH-main, ZH-quadruple |
| TBO           | public test only    | 3200 / 800  | EN-main               |

Table 1: Datasets used in the experiments. TBO is repartitioned from its public test set with seed=20260415.

| API zero-shot model | EN    | ZH    |
|---------------------|-------|-------|
| DeepSeek-v4-Pro     | 23.18 | 22.80 |
| GPT-5.4             | 21.01 | 28.13 |

Table 2: Full-test average scores for the added API zero-shot baselines.

| (a) ZH-main               |              |              |              |              |              |              |              |              |              |
|---------------------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|
| Model                     | Target       |              | Argument     |              | T-A Pair     |              | T-A-H Tri.   |              | Avg.         |
|                           | Hard         | Soft         | Hard         | Soft         | Hard         | Soft         | Hard         | Soft         |              |
| Local LLMs                |              |              |              |              |              |              |              |              |              |
| 0-shot-Qwen3-14B          | 45.49        | <u>54.97</u> | 16.24        | 46.99        | 10.62        | 32.73        | 7.65         | 23.93        | 29.83        |
| SPAR-Qwen3-14B (mainline) | <b>48.73</b> | <b>55.75</b> | <b>21.03</b> | 56.85        | <b>12.36</b> | <u>34.14</u> | <u>8.71</u>  | 24.97        | <b>32.82</b> |
| SPAR-Qwen3.5-35B          | <u>45.84</u> | 53.12        | <u>20.09</u> | <b>57.95</b> | <u>11.23</u> | <b>35.87</b> | <b>9.26</b>  | <b>27.24</b> | <u>32.58</u> |
| API Models                |              |              |              |              |              |              |              |              |              |
| few-shot-DeepSeek-v4-Pro  | 52.69        | 63.08        | 17.86        | 61.03        | 13.62        | 39.53        | 10.75        | 31.09        | 36.21        |
| few-shot-GPT-5.4          | <u>54.17</u> | <u>65.83</u> | 18.87        | <b>62.10</b> | 13.82        | <u>43.90</u> | 10.60        | 31.47        | 37.60        |
| SynChain-DeepSeek-v4-Pro  | 38.92        | 48.68        | 11.54        | 49.57        | 5.09         | 31.89        | 3.75         | 23.75        | 26.65        |
| SynChain-GPT-5.4          | 34.89        | 43.15        | 11.52        | 45.63        | 5.38         | 30.28        | 4.04         | 21.98        | 24.61        |
| Dance-DeepSeek-v4-Pro     | 53.19        | 62.77        | 19.34        | 57.40        | 15.75        | 41.52        | 12.55        | 32.47        | 36.87        |
| Dance-GPT-5.4             | 51.99        | 60.73        | <u>23.89</u> | 57.72        | <b>19.32</b> | <u>44.56</u> | <b>13.63</b> | <u>33.99</u> | <u>38.23</u> |
| SPAR-DeepSeek-v4-Pro      | <b>56.80</b> | <b>65.96</b> | <b>24.03</b> | <u>62.06</u> | 17.27        | <u>44.13</u> | 13.01        | 32.88        | <b>39.52</b> |
| SPAR-GPT-5.4              | 52.62        | 61.94        | 23.12        | 56.62        | <u>17.42</u> | <b>45.48</b> | <u>13.32</u> | <b>34.38</b> | 38.11        |

| (b) EN-main               |              |              |              |              |              |              |              |  |
|---------------------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--|
| Model                     | Target       | Argument     | Targeted     | NTA          | TA           | Harm         | Avg.         |  |
| Local LLMs                |              |              |              |              |              |              |              |  |
| 0-shot-Qwen3-14B          | 32.41        | 46.48        | 25.06        | 14.91        | 11.06        | 47.61        | 29.59        |  |
| SPAR-Qwen3-14B (mainline) | <u>43.45</u> | <u>47.96</u> | <u>34.68</u> | <b>20.96</b> | <b>18.68</b> | <u>59.31</u> | <u>37.51</u> |  |
| SPAR-Qwen3.5-35B          | <b>46.49</b> | <b>50.22</b> | <b>35.43</b> | <u>20.28</u> | <u>16.72</u> | <b>60.11</b> | <b>38.21</b> |  |
| API Models                |              |              |              |              |              |              |              |  |
| few-shot-DeepSeek-v4-Pro  | 36.26        | 42.40        | 22.12        | 3.09         | 1.73         | 53.98        | 26.60        |  |
| few-shot-GPT-5.4          | 38.94        | 44.02        | 13.50        | 4.00         | 2.61         | 48.16        | 25.21        |  |
| SynChain-DeepSeek-v4-Pro  | 38.70        | 41.22        | 18.26        | 2.85         | 2.58         | <b>58.00</b> | 26.94        |  |
| SynChain-GPT-5.4          | 36.60        | 37.52        | 15.56        | 4.76         | 3.52         | 51.92        | 24.98        |  |
| Dance-DeepSeek-v4-Pro     | 45.67        | 36.08        | 27.43        | 2.92         | 2.61         | 56.44        | 28.53        |  |
| Dance-GPT-5.4             | <u>46.15</u> | 42.39        | 24.92        | 8.88         | 7.75         | 52.62        | 30.45        |  |
| SPAR-DeepSeek-v4-Pro      | <b>51.31</b> | <b>50.36</b> | <b>30.02</b> | <b>19.81</b> | <u>13.33</u> | 56.19        | <b>36.84</b> |  |
| SPAR-GPT-5.4              | 42.15        | <u>47.00</u> | <u>29.24</u> | <u>18.84</u> | <b>15.81</b> | <u>56.78</u> | <u>34.97</u> |  |

Table 3: Main results on ZH-main and EN-main. Within each split, the best result in each column is boldfaced and the second-best is underlined.

On the Chinese tracks, Target and Argument evaluate target and argument field parsing. T-A Pair requires the target to be correctly bound to its argument. T-A-H Tri and Quad require the local structure to remain correct after adding the hateful label and, in the four-field task, the group field. For English, the paper follows TBO’s tuple-level evaluation: Target and Argument measure field-level parsing; Targeted requires joint parsing of target and harmfulness; NTA and TA require exact match on  $(target, argument)$  and  $(target, argument, harmful)$  respectively; Harm evaluates harmfulness on the predicted target tuples (Zampieri et al., 2023). Chinese metrics therefore emphasise hard/soft field parsing, whereas English metrics emphasise exact tuple consistency (Bai et al., 2025; Zampieri et al., 2023).

## 4.2 Experimental Setup and Baselines

**Experimental setup** The main local experiments use Qwen3-14B under a dual-24GB-class GPU budget (Yang et al., 2025). Phase 1–3 share the same backbone, with lexicon injection used only for the Chinese Cultural Bystander. Long runs support checkpoint-resume and OOM split-retry. Phase 4 is deterministic aggregation. Sample-level outputs follow the concatenate-first strategy of Section 3.6. Appendix A gives the runtime configuration and artifact map; Appendix D gives the arbitration settings.

**Baselines** The baselines cover direct extraction, task-adapted SynChain and Dance, and SPAR with local and API backbones (Fan et al., 2025; Wang et al., 2026; DeepSeek-AI, 2026; OpenAI, 2026). Table 2 reports the added full-test API zero-shot averages. Prompt templates and baseline adaptations appear in Appendices B and C.

### 4.3 Main Results

Table 3 reports the complete bilingual main-track comparison.

**Main bilingual triplet results** Under a fixed local 14B backbone, SPAR raises the average score on ZH-main from 29.83 to 32.82 and on EN-main from 29.59 to 37.51. The larger gains occur on stricter joint structural metrics.

Qwen3.5-35B records 38.21 on EN-main and 32.58 on ZH-main. Among API systems, SPAR-DeepSeek-v4-Pro records the highest ZH-main average (39.52), while SPAR-GPT-5.4 records EN NTA/TA scores of 18.84/15.81.

**Chinese quadruple extension** The Chinese four-field extension (ZH-quadruple) retains the group field as a test of adaptation to language-specific schema. Full results appear in Appendix Table 25.

**Cross-model observations** The largest differences occur on Targeted, NTA, and TA for English and on T-A Pair, T-A-H Tri, and Quad for Chinese. Appendix F provides additional outputs and cases.

### 4.4 Framework Analysis

**Integrated-prompt controls** Four full-test integrated-prompt controls fix the Phase 1 focus units and place all three perspective descriptions in one call. The Chinese controls retain the same lexicon access. Table 4 reports lower strict tuple-binding scores after removing separated role outputs, candidate clustering, and auditor arbitration. GPT-5.4 Target scores are 46.01 for integrated prompting and 42.15 for SPAR on EN, with corresponding ZH scores of 54.40 and 52.62.

**Component ablations** Table 5 summarises the most diagnostic hard and exact metrics; complete results are deferred to Appendix H.

**Phase-wise ablations** Removing the segmenter raises Chinese Target Hard F1 from 48.73 to 52.34 and lowers T-A-H Tri Hard F1 from 8.71 to 7.02. On English, Target F1 rises from 43.45 to 46.95, while TA and Harm fall. Removing Phase 3 lowers the ZH and EN averages to 31.71 and 36.72.

**Role-wise ablations** Removing the bystander changes the Chinese average from 32.82 to 32.85 and lowers T-A Pair Hard and T-A-H Tri Hard. Removing the moderator lowers English TA from 18.68 to 17.51, while NTA changes from 20.96 to 21.34.

| Backbone        | Track         | Integrated    | SPAR          |
|-----------------|---------------|---------------|---------------|
| DeepSeek-v4-Pro | EN NTA / TA   | 4.87 / 3.89   | 19.81 / 13.33 |
| GPT-5.4         | EN NTA / TA   | 11.41 / 8.18  | 18.84 / 15.81 |
| DeepSeek-v4-Pro | ZH TA / TAH-H | 6.31 / 4.40   | 17.27 / 13.01 |
| GPT-5.4         | ZH TA / TAH-H | 14.08 / 10.56 | 17.42 / 13.32 |

Table 4: Full-test fixed-Phase-1 integrated-prompt controls. The integrated condition retains the three lens descriptions (and Chinese lexicon access) but removes separated candidates, clustering, and auditor arbitration.

| (a) ZH-main          |       |       |       |       |       |  |
|----------------------|-------|-------|-------|-------|-------|--|
| Setting              | Tgt-H | Arg-H | TA-H  | TAH-H | Avg.  |  |
| Qwen3-14B (mainline) | 48.73 | 21.03 | 12.36 | 8.71  | 32.82 |  |
| w/o P1 segmenter     | 52.34 | 15.20 | 9.26  | 7.02  | 32.25 |  |
| w/o P2 victim        | 50.40 | 15.95 | 10.53 | 7.63  | 31.16 |  |
| w/o P2 moderator     | 49.90 | 16.51 | 10.86 | 7.75  | 31.77 |  |
| w/o P2 bystander     | 50.18 | 16.10 | 10.50 | 8.20  | 32.85 |  |
| w/o P3 arbitration   | 46.54 | 17.03 | 10.67 | 7.68  | 31.71 |  |

| (b) EN-main          |       |       |       |       |       |  |
|----------------------|-------|-------|-------|-------|-------|--|
| Setting              | Tgt   | NTA   | TA    | Harm  | Avg.  |  |
| Qwen3-14B (mainline) | 43.45 | 20.96 | 18.68 | 59.31 | 37.51 |  |
| w/o P1 segmenter     | 46.95 | 20.65 | 18.04 | 57.21 | 37.34 |  |
| w/o P2 victim        | 44.70 | 21.18 | 17.20 | 57.21 | 37.02 |  |
| w/o P2 moderator     | 44.29 | 21.34 | 17.51 | 59.11 | 37.43 |  |
| w/o P3 arbitration   | 43.66 | 20.42 | 17.81 | 57.61 | 36.72 |  |

Table 5: Ablation summary on the bilingual main tracks. The main text keeps only the most diagnostic hard/exact metrics; complete bilingual ablation results appear in Appendix H.

**Diagnostic validation** Supplementary exact-set and blinded semantic diagnostics appear in Appendix E. They are reported as secondary checks, not primary ranking metrics. The attacked-group breakdown in the same appendix locates a remaining multi-group binding error.

### 4.5 Distillation Results

Table 6 compares the distilled 4B student with the zero-shot and SPAR-Qwen3-14B systems on all three evaluation tracks.

The distilled student improves over SPAR-Qwen3-14B on both Chinese tracks and remains close to its teacher on EN-main, despite using a substantially smaller backbone. Appendix G reports teacher-trace construction, filtering, and student training.

| (a) ZH-main               |       |       |       |
|---------------------------|-------|-------|-------|
| Model                     | TAH-H | TAH-S | Avg.  |
| 0-shot-Qwen3-14B          | 7.65  | 23.93 | 29.83 |
| SPAR-Qwen3-14B (mainline) | 8.71  | 24.97 | 32.82 |
| Distillation-Qwen3-4B     | 8.33  | 26.04 | 33.67 |

| (b) EN-main               |       |       |       |
|---------------------------|-------|-------|-------|
| Model                     | TA    | Harm  | Avg.  |
| 0-shot-Qwen3-14B          | 11.06 | 47.61 | 29.59 |
| SPAR-Qwen3-14B (mainline) | 18.68 | 59.31 | 37.51 |
| Distillation-Qwen3-4B     | 18.50 | 59.05 | 37.33 |

| (c) ZH-quadruple          |        |        |       |
|---------------------------|--------|--------|-------|
| Model                     | Quad-H | Quad-S | Avg.  |
| 0-shot-Qwen3-14B          | 6.87   | 19.42  | 25.70 |
| SPAR-Qwen3-14B (mainline) | 6.18   | 22.37  | 28.95 |
| Distillation-Qwen3-4B     | 7.04   | 25.05  | 30.38 |

Table 6: Distillation summary across the three evaluation tracks.

## 4.6 Qualitative Analysis

**Case study** Table 7 traces three Phase 1 local focus units from a Chinese multi-target example. Phase 2 produces conflicting labels for  $g_2$  and  $g_3$ , and Phase 3 selects the gold label for both units. For  $g_1$ , SPAR retains the full argument “poor; populous”, which SynChain truncates.

| Item      | Content                                                                                                                                                                                                                                               |
|-----------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Text      | First impression: Henan is poor and populous; Northeast China has one of the world’s lowest birth rates; public security in Xinjiang may not be very good.                                                                                            |
| Gold      | $g_1$ : (Henan, “poor; populous”, 1)<br>$g_2$ : (Northeast China, one of the world’s lowest birth rates, 1)                                                                                                                                           |
| Phase 1   | $g_3$ : (Xinjiang, public security may not be very good, 1)<br>$g_1$ : Henan: poor; populous<br>$g_2$ : Northeast China: one of the world’s lowest birth rates<br>$g_3$ : Xinjiang: public security may not be very good                              |
| Phase 2   | $g_1$ : only hateful candidates remain.<br>$g_2$ : (Northeast China, one of the world’s lowest birth rates, 1/0).                                                                                                                                     |
| Phase 3   | $g_3$ : (Xinjiang, public security may not be very good, 1/0).<br>$g_1$ : (Henan, “poor; populous”, 1)<br>$g_2$ : (Northeast China, one of the world’s lowest birth rates, 1)                                                                         |
| Baselines | $g_3$ : (Xinjiang, public security may not be very good, 1)<br>$g_1$ : Dance is correct. SynChain outputs (Henan, poor, 0), missing “populous”.<br>$g_2$ : Dance and SynChain both assign label 0.<br>$g_3$ : Dance and SynChain both assign label 0. |

Table 7: Phase-wise processing of three local focus units.  $g_1$ ,  $g_2$ , and  $g_3$  denote Phase 1 units. One unit may yield several sample-level tuples after Phase 4. The Chinese input is shown in English translation.

**Error analysis** The main residual error is argument boundary over-expansion. In Table 8, SPAR-Hate predicts the correct target and harmfulness but retains additional contextual material, so the prediction receives no tuple credit under exact match. Appendix F provides further cases.

| Item           | Content                                                                                           |
|----------------|---------------------------------------------------------------------------------------------------|
| Text           | some of y’all aren’t being held accountable for the dumb shit that y’all be doing....and it shows |
| Gold           | (y’all, dumb shit, 1)                                                                             |
| SPAR-Qwen3-14B | (y’all, dumb shit that y’all be doing, 1); (null, it shows, 0)                                    |

Table 8: A remaining SPAR-Hate error: overly wide argument boundaries.

## 5 Conclusion

SPAR-Hate combines local focus-unit segmentation, role-conditioned generation, constrained auditor arbitration, and sample-level reassembly. Its largest gains occur on stricter joint structural metrics under the controlled benchmark settings. Integrated-prompt controls record lower tuple-binding scores after collapsing perspective generation and arbitration into one call. The Chinese four-field extension and distillation results cover language-specific schema and structured teacher traces.

## Limitations

Evaluation covers Chinese and English and omits a full comparison with task-specific fine-tuned systems. The task-motivated role set has not been exhaustively searched, and the lexicon has no complete removal ablation. Weak lexical context can still over-flag dialectal, culturally loaded, or reclaimed terms. The threshold replay, blind audit, and attacked-group breakdown have limited scope and cannot support broad claims about statistical optimality, fairness, or cultural validity. TBO results use the deterministic internal split and do not support direct comparison with results on the original public test-only release.

## Ethical Considerations

This study uses public Chinese and English benchmark datasets to examine structured hate speech parsing. Their contents include abusive, discriminatory, and potentially traumatic expressions. The paper retains only representative examples needed for the academic argument and recommends a minimal-exposure principle in data processing, visualisation, and manual analysis to reduce secondary harm to researchers, annotators, and readers.

Such systems also carry misuse risks, including over-censorship, automated punishment, and

large-scale opinion monitoring. Earlier work shows that false positives can arise from ambiguous boundaries between offensive language and hate speech, spurious correlations around minority-group mentions, and model fragility on functional phenomena (Davidson et al., 2017; Hartvigsen et al., 2022; Röttger et al., 2021). Structured outputs and traceable intermediate processes increase transparency, but they may also increase the operational reach of deployed moderation systems. Real-world deployment therefore requires human review, appeals, threshold calibration, error auditing, and continuing bias evaluation across languages, groups, and cultural settings.

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## A Implementation and Artifact Details

Table 9 gives the retained Qwen3-14B configuration (Yang et al., 2025). Phase 1–3 share the same local backbone, and Phase 4 is deterministic. The compact profile uses vLLM (Kwon et al., 2023).

| Item                    | Value                                                                                     |
|-------------------------|-------------------------------------------------------------------------------------------|
| Backbone                | Qwen3-14B                                                                                 |
| Hardware                | RTX 3090 + RTX 4090D                                                                      |
| Precision               | bfloat16                                                                                  |
| Context length          | 8192                                                                                      |
| Tensor parallelism      | 2                                                                                         |
| Phase 1                 | local focus-unit segmentation; batch 4                                                    |
| Phase 2                 | 3 roles; micro-batch 64; Chinese bystander with lexicon injection                         |
| Phase 3                 | quality threshold 0.60; cluster similarity 0.66; auditor enabled; max retained clusters 2 |
| Runtime safeguards      | checkpoint resume; OOM split-retry                                                        |
| Compact service profile | vLLM backend; auditor batch 1; re-generation disabled                                     |
| Phase 4                 | deterministic reassembly                                                                  |

Table 9: Main local configuration for the reported Qwen3-14B mainline.

### A.1 Runtime and Call Diagnostics

Retained EN, ZH-main, and ZH-quadruple runs take 499.0, 617.6, and 623.3 minutes. Phase 2

makes 4,524, 6,978, and 6,933 role calls at 0.25–0.28 role-groups per second. Auditor refinement is triggered for 982, 1,645, and 1,610 groups. These figures describe retained runs; incomplete billing logs preclude a monetary cost estimate.

### A.2 Artifact Map and Recoverability

The artifact roots SPAR/, SPAR\_anonymous\_submission/, and transfer\_bundles/ contain the deterministic TBO split and Phase 0 preparation path, Phase 1–3 prompts and configurations, Phase 3 scoring and fallback code, direct and API baseline outputs, SynChain and Dance adaptations, diagnostic summaries, and teacher/student exports. Historical bilingual distillation records are partly archival. Preserved reports and official evaluation exports support the reported construction and evaluation statistics, while the Chinese student bundle retains the independently recoverable training example.

## B Prompt Templates

The three Phase 2 roles share the output contract, Target Resolution, Non-empty Argument, Output Sequence, Short Rationale, and Current Task blocks. Figure 4 gives the Victim instruction body and example headers. The Moderator and Cultural Bystander figures retain their role-specific additions. Repeated example titles are omitted.

### Phase 1 Segmenter

```
# Role
You are the SPAR-Hate Segment Agent specializing in English text.
Your ONLY output is a strict JSON array.

# Rules
1. Divide by target and intent: Split the text into separate groups if
different targets are attacked or distinct intents exist.
2. Context isolation: group_text MUST be copied EXACTLY from the
original text as a meaningful local context. Do not paraphrase, summarize,
or alter punctuation/emojis.
3. Target normalization: canonical_target is the direct entity mention.
If the target is strictly absent, unmentioned, or null, output
"IMPLICIT_TARGET".
4. Output scope: ONLY output local_group_id, group_text, and
canonical_target.

# Examples
Example 1 (Multi-Target Segmentation)
Example 2 (Null/Implicit Targets & General Venting)
Example 3 (Non-harmful / Object Target with Emojis)

# Current Task
Original text: {{TEXT}}
Output: [
```

Figure 3: Excerpt of the English Phase 1 segmenter prompt used in the bilingual main tracks.



### Phase 3 Auditor

#### ## Role

You are the SPAR-Hate Phase-3 Arbitrate Auditor for English. You do not perform crude majority vote. You arbitrate between role evidence, candidate clusters, triage signals, and dynamic beacons to select the final tuple most likely to match the English ground truth. Your ONLY output is a strict JSON object.

#### ## English Task Rules

1. Ground the final answer in focus\_text. final\_argument must be an exact or near-exact substring from the focus span.
2. Prefer final\_target from inside the focus span. Only use canonical\_target or outside context when the focus span is fragmentary, pronominal, or missing the subject.
5. Distinguish reclaimed slang, quotation, refutation, irony, and performative speech from genuine targeted harm.
7. If one role misses coded derogation or over-penalizes a reclaimed or quoted expression, say so compactly in fused\_rationale and correction\_trace.
9. If several candidates differ mainly in argument length, prefer the shortest span that still independently expresses the attack core.

#### ## Few-shot example headers

Example 1: clear group generalization, final harmful  
 Example 2: reclaimed slang, final non-harmful  
 Example 3: shrink an over-broad argument span

Figure 8: Rendered excerpt of the English Phase 3 auditor prompt used in the mainline configuration.

## C Baseline Adaptation

SynChain and Dance are modified only enough to produce hate tuples compatible with the benchmarks. The aim is to preserve each method’s high-level inductive bias rather than rewrite it into a new multi-stage system (Fan et al., 2025; Wang et al., 2026).

**General adaptation.** Across all baselines, the adaptation layer makes only three minimal changes. First, raw outputs are normalised into strict JSON readable by the official evaluation scripts. Second, field names and label spaces are aligned: English uses harmful, Chinese uses hateful, and group is enabled only on the Chinese four-field track. Third, lightweight post-processing is applied only where required by the evaluation interface, including boundary cleaning, duplicate tuple removal, and unified sample-level export. None of these operations adds candidate arbitration or reranking.

**SynChain.** The syntax-aware extraction bias is retained. The adapted workflow still generates structure-sensitive candidates first, then resolves target, argument, and label, and finally maps intermediate candidates back to scorable text fields. Beyond alignment to the output contract, no extra multi-role generation, auditor arbitration, or lexicon weighting is added.

**Dance.** The divide-and-conquer skeleton of grouping, per-group inference, and merge is re-

tained. The adapted system still performs inference over local groups before returning to sample-level outputs. The only change is that the internal extraction target is rewritten from aspect/opinion/sentiment-style fields into hate tuples. As with SynChain, no extra SPAR-style arbitration or lexicon-aware reranking is added.

## D Auditor Scoring and Bounded Arbitration

Phase 3 scores, clusters, routes, and selects role candidates under grounding constraints. Table 10 gives the main settings, and Table 11 gives the scoring signals.

| Item               | Value                                                                   |
|--------------------|-------------------------------------------------------------------------|
| Role set           | victim / moderator / cultural_bystander                                 |
| Quality threshold  | 0.60                                                                    |
| Cluster similarity | 0.66                                                                    |
| Similarity weights | target/argument/label/group = 0.45/0.45/0.05/0.05                       |
| Score bonuses      | support role 0.12; candidate lexicon 0.05; cluster lexicon 0.08         |
| Auditor lanes      | consensus / defective / conflict / lexicon-hit / victim-microaggression |
| Auditor batch      | 2 (main 14B); 1 (compact v11m)                                          |
| Regeneration       | enabled (main 14B); disabled (compact v11m)                             |
| Cluster retention  | max 2; score floor 1.05; min support roles 2                            |
| Decoding profile   | bf16; TP=2; context 8192                                                |
| Final selection    | deterministic fallback after optional refinement                        |

Table 10: Key Phase 3 settings in the local 14B arbitration configurations.

| Feature group         | Signal                                                 |
|-----------------------|--------------------------------------------------------|
| Grounding             | argument in focus text; no invented evidence           |
| Target anchoring      | explicit target; canonical-target match                |
| Structural validity   | JSON validity; legal label; track-compatible fields    |
| Group-label coherence | group-label consistency in ZH-quadruple                |
| Soft priors           | lexicon bonus; moderator floor; victim microaggression |

Table 11: Main feature groups used by the Phase 3 candidate scorer.

The quality threshold of 0.60 filters weak or ungrounded candidates before clustering. The similarity threshold of 0.66 limits merges between candidates with divergent target or argument fields. Both values are reused across the reported languages and benchmarks.

| Step     | Operation                                                | Bound                  |
|----------|----------------------------------------------------------|------------------------|
| Validate | Check JSON, label, argument grounding, and target anchor | quality $\geq 0.60$    |
| Cluster  | Compare target, argument, label, and optional group      | similarity $\geq 0.66$ |
| Route    | Assign consensus, defective, or conflict lane            | one local unit         |
| Refine   | Apply soft beacons and optional auditor call             | one regeneration       |
| Select   | Rank with deterministic fallback                         | at most two clusters   |

Table 12: Operational summary of local Phase 3 arbitration.

| Measure                        | Retained-run summary |
|--------------------------------|----------------------|
| Raw-cluster p95                | EN 3; ZH 4           |
| Retained/final p95 and maximum | 2                    |
| Conflict-lane share            | 55.9–61.7%           |
| Auditor-use share              | 65.1–70.7%           |

Table 13: Boundedness and routing diagnostics across the retained runs.

## E Robustness and Semantic Validation

### E.1 Threshold Sensitivity

The actual auditor is replayed on fixed seed-10947 subsets of 200 complete samples per language, covering 385 EN and 281 ZH focus groups per setting. Quality varies over 0.55/0.60/0.65 at similarity 0.66. Similarity varies over 0.60/0.66/0.72 at quality 0.60. All other settings remain fixed. Table 14 reports the retained summary.

| Language | Observed range | Default |
|----------|----------------|---------|
| EN       | 34.97–35.08    | 35.08   |
| ZH       | 26.28–27.12    | 26.82   |

Table 14: Four-hard-metric averages in the fixed-subset threshold replay. The results are not full-test significance estimates.

### E.2 Blind Semantic Audit

Two independent bilingual or native-speaker reviewers assess 60 stratified Chinese focus units with gold labels hidden. Separate final-tuple and Cultural-Bystander-rationale rubrics yield 120 judgements. Table 15 gives acceptance and agreement. Consensus cases reach 70% strict overall acceptance; disagreement-heavy lexicon–auditor cases receive lower acceptance.

### E.3 Strict Sample Exact-Set Summary

### E.4 Attacked-Group Breakdown

Table 17 reports ZH-quadruple scores by gold attacked group. The Racism+Sexism group has the largest TAH-to-Quad drop, locating the main loss in multi-group binding. The breakdown measures

| Object              | R1   | R2   | Agree. | $\kappa$ |
|---------------------|------|------|--------|----------|
| Final tuple         | 73.3 | 71.7 | 81.7   | 0.540    |
| Bystander rationale | 68.3 | 58.3 | 86.7   | 0.716    |

Table 15: Acceptance rates, percentage agreement, and Cohen’s  $\kappa$  in the blind semantic audit.

| Track   | SPAR-DeepSeek    | Direct references           |
|---------|------------------|-----------------------------|
| EN      | 20/800 (2.50%)   | 0–9/800 (0.00–1.13%)        |
| ZH-main | 141/1605 (8.79%) | zero-shot: 37/1605; 66/1605 |

Table 16: Sample exact-set summary. Some ZH few-shot baselines exceed the SPAR-DeepSeek value.

robustness across the annotated groups; fairness requires separate evidence.

| Gold group      | Samples | TAH-S | Quad-S |
|-----------------|---------|-------|--------|
| Sexism          | 302     | 36.66 | 34.49  |
| Racism          | 223     | 40.56 | 35.57  |
| Region          | 216     | 27.20 | 24.93  |
| LGBTQ           | 93      | 34.75 | 32.13  |
| Racism + Sexism | 85      | 21.85 | 5.30   |

Table 17: ZH-quadruple attacked-group diagnostic. Scores are Soft F1 and groups are defined from gold labels.

## F Qualitative Cases and Error Analysis

The Chinese case isolates a target conflict. The English case traces a conflict-lane decision within a multi-target sample.

In this case, Victim and Cultural Bystander both identify the attacking target as “Beijingers”, whereas Moderator shifts the target to the mentioned victim group. The auditor follows the grounded consensus on the focus text and downweights the moderator reading.

The current text is focus unit  $g_2$  in a sample containing  $g_1$ ,  $g_2$ , and  $g_3$ . Phase 4 retains two harmful tuples from  $g_1$ , (shit, shit, 1) from  $g_2$ , and one non-harmful tuple from  $g_3$ . One focus unit can emit several tuples. For  $g_2$ , the auditor selects the Victim reading and downweights the non-harmful Moderator and Cultural Bystander candidates.

| Field              | Content                                                                                       |
|--------------------|-----------------------------------------------------------------------------------------------|
| Text               | The people spreading the claim that Henan people steal manhole covers are in fact Beijingers. |
| Gold tuple         | (Beijingers, saying that Henan people steal manhole covers, 1)                                |
| Victim             | (Beijingers, saying that Henan people steal manhole covers, 1)                                |
| Moderator          | (Henan people, steal manhole covers, 1)                                                       |
| Cultural Bystander | (Beijingers, saying that Henan people steal manhole covers, 1)                                |
| Triage             | lane=conflict;<br>initial_conflict=target_conflict                                            |
| Beacons            | grounding; consensus                                                                          |
| Correction trace   | moderator: downweighted for misreading the victim mention as the attacking target             |
| Final tuple        | (Beijingers, saying that Henan people steal manhole covers, 1)                                |

Table 18: Chinese case study showing target-conflict resolution in Phase 3.

| Field                              | Content                                                                                             |
|------------------------------------|-----------------------------------------------------------------------------------------------------|
| Text                               | <i>that shit is not cute &amp; dnt make u hard.</i>                                                 |
| Phase 4 restored sample prediction | (bitches, Ghetto, 1); (bitches, ignorant, 1);<br>(shit, shit, 1); (IMPLICIT_TARGET, alldat shit, 0) |
| Victim                             | (shit, shit, 1)                                                                                     |
| Moderator                          | (u, dnt make u hard, 1)<br>(IMPLICIT_TARGET, that shit, 0)                                          |
| Cultural Bystander                 | (IMPLICIT_TARGET, dnt make u hard, 0)<br>(shit, shit, 0)                                            |
| Triage                             | lane=conflict                                                                                       |
| Beacons                            | grounding, victim_microaggression                                                                   |
| Correction trace                   | moderator: downweighted;<br>cultural_bystander: downweighted                                        |
| Final tuple                        | (shit, shit, 1)                                                                                     |

Table 19: English case study showing conflict-lane arbitration inside a multi-target sample.

## G Distillation Data and Student Training

### G.1 Teacher-trace Schema

The distillation target includes more than the final tuple. Each training row also preserves intermediate decomposition, role candidates, conflict diagnosis, and the final arbitration result, so that the student learns a structured decision process rather than only the flat output surface.

### G.2 Filtering and Dataset Statistics

The bilingual statistics come from the main distillation construction run. The pipeline has three steps: first, retain train rows with recoverable identifiers and serialisable teacher packages; second, build a strict HQ reasoning subset using groundedness, final tuple validity, and audit confidence; third, expand it under the same grounding constraints into reasoning-plus and JSON-only variants for curriculum training.

### G.3 A Real Constructed Training Example

Table 22 shows one real final training row from the released Chinese student bundle. The sample

| Field group          | Content                                                                    |
|----------------------|----------------------------------------------------------------------------|
| Identifiers          | sample_id, group_id, source, split, language                               |
| Source text          | original text and the current focus/group unit                             |
| Focus evidence       | group_text, focus_text, canonical_target                                   |
| Role evidence        | tuples from the three roles, short rationales, quality scores, lexicon hit |
| Conflict diagnosis   | triage lane, field conflicts, applied beacons, clusters                    |
| Teacher decision     | teacher_final_tuple, teacher_rationale, audit confidence                   |
| Supervision messages | system instruction, user evidence package, assistant supervision target    |

Table 20: Schema of the final constructed distillation rows.

| Stage                  | Count    | Note                                                  |
|------------------------|----------|-------------------------------------------------------|
| Phase 3 group traces   | 7,752    | all available local decision traces                   |
| Packaged train rows    | 3,739    | base samples entering the teacher package             |
| Teacher reasoning HQ   | 2,221    | main warm-up variant                                  |
| HQ Chinese rows        | 1,590    | zh_group_hateful                                      |
| HQ English rows        | 631      | en_span_harmful                                       |
| Teacher reasoning plus | 3,194    | reasoning variant with relaxed conflict threshold     |
| Teacher JSON-only plus | 3,194    | final JSON-aligned variant                            |
| Validation checks      | all pass | duplicate id 0; schema error 0; invalid final tuple 0 |

Table 21: Summary statistics for the teacher-trace construction pipeline.

comes from a multi-target Chinese input, but the current training row supervises only the second focus unit. The three role rationales are retained so that the student learns argument anchoring when targets agree but arguments compete.

### G.4 Student Training Setup

| Item                   | Value                                                                |
|------------------------|----------------------------------------------------------------------|
| Student backbone       | Qwen3-4B-Instruct-2507                                               |
| Prompt template        | Qwen3 no-think                                                       |
| Training split         | train only                                                           |
| Supervision regime     | teacher-only                                                         |
| Curriculum stages      | teacher reasoning HQ; teacher reasoning plus; teacher JSON-only plus |
| Epochs per stage       | 1.0 / 1.0 / 1.0                                                      |
| Sequence length        | 4096                                                                 |
| Per-device batch size  | 1                                                                    |
| Gradient accumulation  | 8                                                                    |
| Optimizer and schedule | learning rate 1e-4; cosine; warmup ratio 0.05                        |
| Precision              | bf16                                                                 |
| Adaptation method      | QLoRA (4-bit BnB)                                                    |
| LoRA setting           | rank 32; alpha 32; dropout 0.0                                       |

| Field               | Content                                                                                                                                                                                                                                                                                  |
|---------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Source text         | Marriage is a necessity for women. Men can stay unmarried for life, but women cannot. In reality, countless men are even more eager. They will empty the family savings and act like simps just to marry and have children. Absurd.                                                      |
| Sample-level gold   | (marriage, a necessity for women, 1); (countless men, empty the family savings and act like simps just to marry and have children, 1)                                                                                                                                                    |
| Current focus       | In reality, countless men are even more eager. They will empty the family savings and act like simps just to marry and have children. Absurd.                                                                                                                                            |
| Dataset variant     | teacher_trace_reasoning_hq                                                                                                                                                                                                                                                               |
| Victim              | tuple: (men, even more eager than women, and willing to empty the family savings and act like simps just to marry and have children, harmful); rationale: It describes men as simps and derides their behaviour, carrying clear gender stereotyping and disparagement.                   |
| Moderator           | tuple: (men, willing to empty the family savings and act like simps just to marry and have children, harmful); rationale: The focus uses derogatory wording such as "simps" to negatively characterise men. The phrasing is attacking and demeaning, which violates community standards. |
| Cultural Bystander  | tuple: (men, act like simps, harmful); rationale: [Lexicon Hit] "simp" is used here to belittle men and suggest a lack of dignity.                                                                                                                                                       |
| Conflict diagnosis  | lane=consensus; high-risk field=argument; error tags=lexicon_hit, auditor_span_refined                                                                                                                                                                                                   |
| Teacher final tuple | target=men; argument=act like simps; group=unknown; harmful=1; direction=harmful                                                                                                                                                                                                         |
| Assistant target    | format: reasoning+JSON; final JSON: target=men; argument=act like simps; group=unknown; harmful=1; direction=harmful                                                                                                                                                                     |

Table 22: A condensed real training row from the constructed distillation data.

Table 23: Student-model training setup used in the distillation pipeline.

Student training follows a teacher-only curriculum. Stage 1 uses the strict HQ reasoning subset to establish the structured decision process. Stage 2 expands coverage with reasoning-plus. Stage 3 aligns the model to strict JSON output. Under this protocol, training uses only the train split, ground truth is never used as assistant supervision, evaluation is limited to teacher reasoning and teacher JSON, and manual prefill is disallowed. The Qwen3-4B backbone, 4-bit QLoRA, and LoRA rank/alpha settings follow the corresponding parameter-efficient fine-tuning methods (Yang et al., 2025; Dettmers et al., 2023; Hu et al., 2021).

## H Full Bilingual Ablation Results

Table 24 gives the complete bilingual ablations underlying the compact analysis in Section 4.4.

| (a) ZH-main          |        |       |          |       |          |       |            |       |       |  |
|----------------------|--------|-------|----------|-------|----------|-------|------------|-------|-------|--|
| Setting              | Target |       | Argument |       | T-A Pair |       | T-A-H Tri. |       | Avg.  |  |
|                      | Hard   | Soft  | Hard     | Soft  | Hard     | Soft  | Hard       | Soft  |       |  |
| Qwen3-14B (mainline) | 48.73  | 55.75 | 21.03    | 56.85 | 12.36    | 34.14 | 8.71       | 24.97 | 32.82 |  |
| w/o phase1 segmenter | 52.34  | 64.46 | 15.20    | 48.92 | 9.26     | 34.43 | 7.02       | 26.39 | 32.25 |  |
| w/o phase2 victim    | 50.40  | 60.67 | 15.95    | 46.48 | 10.53    | 32.84 | 7.63       | 24.78 | 31.16 |  |
| w/o phase2 moderator | 49.90  | 60.07 | 16.51    | 47.65 | 10.86    | 34.91 | 7.75       | 26.49 | 31.77 |  |
| w/o phase2 bystander | 50.18  | 61.11 | 16.10    | 50.90 | 10.50    | 36.93 | 8.20       | 28.90 | 32.85 |  |
| w/o phase3           | 46.54  | 56.64 | 17.03    | 51.42 | 10.67    | 36.58 | 7.68       | 27.10 | 31.71 |  |

| (b) EN-main          |        |       |          |       |       |       |       |
|----------------------|--------|-------|----------|-------|-------|-------|-------|
| Setting              | Target | Arg.  | Targeted | NTA   | TA    | Harm  | Avg.  |
| Qwen3-14B (mainline) | 43.45  | 47.96 | 34.68    | 20.96 | 18.68 | 59.31 | 37.51 |
| w/o phase1 segmenter | 46.95  | 47.11 | 34.06    | 20.65 | 18.04 | 57.21 | 37.34 |
| w/o phase2 victim    | 44.70  | 49.17 | 32.68    | 21.18 | 17.20 | 57.21 | 37.02 |
| w/o phase2 moderator | 44.29  | 48.25 | 34.07    | 21.34 | 17.51 | 59.11 | 37.43 |
| w/o phase2 bystander | 44.49  | 47.24 | 33.10    | 20.64 | 18.37 | 59.22 | 37.18 |
| w/o phase3           | 43.66  | 46.77 | 34.07    | 20.42 | 17.81 | 57.61 | 36.72 |

Table 24: Complete bilingual Qwen3-14B ablations.

## I Full Results on ZH-quadruple

Table 25 reports the full four-field results used for the Chinese extension discussed in Section 4.3.

| Model                     | Target |       | Argument |       | T-A Pair |       | T-A-H Tri. |       | Quad. |       | Avg.  |
|---------------------------|--------|-------|----------|-------|----------|-------|------------|-------|-------|-------|-------|
|                           | Hard   | Soft  | Hard     | Soft  | Hard     | Soft  | Hard       | Soft  | Hard  | Soft  |       |
| <i>Local LLMs</i>         |        |       |          |       |          |       |            |       |       |       |       |
| 0-shot-Qwen3-14B          | 43.94  | 53.81 | 15.60    | 47.00 | 9.92     | 29.58 | 7.65       | 23.18 | 6.87  | 19.42 | 25.70 |
| SPAR-Qwen3-14B (mainline) | 48.54  | 58.58 | 19.61    | 53.94 | 11.00    | 34.14 | 8.51       | 26.61 | 6.18  | 22.37 | 28.95 |
| SPAR-Qwen3.5-35B          | 50.81  | 60.84 | 19.57    | 52.05 | 13.64    | 38.50 | 10.59      | 29.94 | 8.68  | 24.48 | 30.91 |
| <i>API Models</i>         |        |       |          |       |          |       |            |       |       |       |       |
| LLaMA3-70B*               | 30.87  | 41.45 | 14.80    | 46.68 | 8.29     | 25.38 | 7.40       | 22.58 | 4.72  | 13.14 | 21.53 |
| Claude-3.5-Sonnet*        | 41.45  | 54.06 | 15.80    | 55.80 | 10.43    | 36.96 | 9.28       | 33.04 | 7.10  | 25.22 | 28.91 |
| few-shot-DeepSeek-v4-Pro  | 54.86  | 65.70 | 18.62    | 60.50 | 14.39    | 41.02 | 11.34      | 32.51 | 9.70  | 27.99 | 33.66 |
| few-shot-GPT-5.4          | 52.87  | 64.98 | 17.09    | 60.28 | 12.43    | 42.17 | 9.45       | 31.54 | 8.15  | 27.50 | 32.65 |
| SPAR-DeepSeek-v4-Pro      | 52.66  | 61.29 | 23.73    | 65.66 | 16.45    | 43.12 | 12.70      | 32.25 | 10.82 | 27.65 | 34.63 |
| SPAR-GPT-5.4              | 52.15  | 60.63 | 21.69    | 55.34 | 16.37    | 43.71 | 13.15      | 33.40 | 11.63 | 29.11 | 33.72 |

Table 25: Full Chinese four-field results. Starred rows are historical STATE-ToxicCN values (Bai et al., 2025).