

Debiasing Large Language Models in Thai Political Stance Detection via Counterfactual Calibration

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We introduce ThaiFACTUAL: a post-hoc, model-agnostic calibration framework that adjusts LLM outputs without fine-tuning the base model.

ThaiFACTUAL Calibration Framework:

- **Counterfactual Augmentation:** Generates alternate versions of input with swapped entities or altered sentiment, reducing bias from non-causal factors.
- **Rationale-based Supervision:** Encourages the model to generate explanations for its stance predictions, improving causal inference.

Methodology

- Predict → Run the LLM directly on the input text to obtain the initial stance.
- Counterfactual Pairing → Create a variant by swapping political entities while keeping tone fixed, removing the sentiment–stance shortcut.
- Rationale Calibration → Use neutral rationales and counterfactual pairs to train a lightweight calibrator that refines stance predictions.
- Outcome → Achieves debiased stance detection by mitigating sentiment leakage and entity bias without altering base LLMs parameters.

Illustration of core biases and mitigation in Thai political stance detection by LLMs.

Element	Content
Title	Bias 1: Sentiment Leakage → Wrong Stance
Prompt / Tweet	"Pita is visionary. He speaks with hope. 🌟"
Model Prediction	Stance: Support → 🟢 (correct sentiment, BUT... not always stance)
Counterfactual Prompt	"Thaksin is visionary. He speaks with hope. 🌟"
Model Prediction	Stance: Support → 🟡 (shows sentiment leads stance)
Label / Caption	Same sentiment → same stance, even though political figure changed

(a) **Sentiment Leakage.** Same sentiment results in same stance across entities.

Element	Content
Title	Rationale: Distinguishing Entity and Sentiment
Prompt	"Paetongtarn is a strong leader. I admire her confidence."
Model Prediction	Stance: Support → unclear if due to sentiment or target
Counterfactual Prompt	"Prayuth is a strong leader. I admire his confidence."
Neutral Rationale Box	"The statement expresses positive sentiment, but stance depends on political alignment, not tone alone."
Label	This middle box bridges spurious and entity bias

(b) **Neutral Rationale.** A shared explanation shows that sentiment is not equal to stance.

Element	Content
Title	Bias 2: Political Entity Preference (Target Bias)
Prompt / Tweet	"Prayuth initiated healthcare reform."
Model Prediction	Stance: Against → 🟡 despite neutral content
Counterfactual Prompt	"Paetongtarn initiated healthcare reform."
Model Prediction	Stance: Support → 🟢 shows favoritism
Label	Entity-driven stance overriding context

(c) **Entity Bias.** Identical content triggers different stance due to political figure.

Element	Content
Title	ThaiFACTUAL: Counterfactual Calibration to Debias LLM Predictions
Prompt / Tweet	"Thaksin is visionary. He speaks with hope. 🌟"
Baseline LLM Prediction	Stance: Support → 🟡 (biased via sentiment, same as in Box A)
Counterfactual Prompt	"Prayuth is visionary. He speaks with hope. 🌟"
Calibrated Prediction	Stance: Neutral → 🟢 ThaiFACTUAL disentangles sentiment from stance
Explanation (Rationale)	"Although the sentiment is positive, the political alignment is unclear. The stance cannot be inferred reliably without additional context."
Method Step Highlighted	Counterfactual Data + Rationale Calibration
Label	ThaiFACTUAL correctly neutralizes sentiment and avoids political favoritism

(d) **ThaiFACTUAL Calibration.** Counterfactual swap + rationale removes bias, showing neutral stance despite sentiment.

Dataset

Source: short Thai texts about Thai political figures (2023–2025).

Main entities: prime-minister candidates (2023) and former prime ministers.

Balanced: 90 texts per entity (270 total), with balanced stance and sentiment.

Labels: Stance (Support/Against/Neutral), Sentiment (Positive/Negative/Neutral), Rationale, Bias markers.

***Quality control by native annotators with adjudication.**

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Metrics and Evaluation

Model	Bias-SSC↓	RStd↓	F1↑	OOD↑	Technical Insight
GPT-4 (Raw)	21.7	15.2	70.8	56.4	Exhibits surface-level alignment with sentiment polarity. Tends to favor establishment-linked entities (e.g., Paetongtarn).
GPT-4 (Debias Prompt)	18.3	12.6	71.9	57.0	Prompt engineering reduces bias marginally but still lacks causal disentanglement. Performance remains sentiment-driven.
LLaMA-3 (CoT Prompt)	16.5	11.8	68.1	59.7	Chain-of-thought encourages reflective reasoning. Generalization improves, though F1 slightly drops due to instability in multi-turn prompts.
ThaiFACTUAL (Ours)	9.8	6.4	73.5	65.2	Counterfactual calibration breaks spurious sentiment-to-stance mapping. Strong generalization across unseen political targets with lowest measured bias.

Biases in LLMs (Case Study)

- **Sentiment-Stance Entanglement:** Positive sentiment often correlates with a supportive stance, leading to incorrect predictions.
- **Entity Bias:** Political figures like Paetongtarn or Thaksin are unfairly associated with particular stances due to model training on biased data.