Low-Resource Safety Failures Are Action Failures, Not Representation Failures

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Abstract

Safety alignment learned in high-resource languages transfers poorly to low-resource languages. Models refuse harmful prompts in English but fail to refuse when the same prompts are translated into Swahili or Burmese. Adaptive steering methods like AdaSteer (Zhao et al., 2025b) and CAST (Lee et al., 2025) inherit this failure cross-lingually. We diagnose where transfer breaks down. Across Qwen2.5-7B, Gemma-2-9B, and Llama-3.1-8B on 23 languages, the harmfulness direction extracted from high-resource activations linearly separates harmful from harmless low-resource prompts nearly as well as high-resource ones. The relevant representation is present. Yet harmful refusal drops from 87.9% to 43.9%. The model fails to convert the representation into refusal. What fails to transfer is calibration of the safety decision, not the underlying representation. We exploit this by recalibrating, rather than retraining, a high-resource gate: a low-rank logistic readout with its decision threshold reset using as few as 1 to 4 target-language examples per class. The gate routes between refusal steering and harmfulness-direction ablation, substantially raising mean refusal selectivity (Δ = harmful − harmless refusal) from 33.6 for the strongest adapted baseline to 54.5 while preserving MMLU utility. These results suggest that some low-resource safety failures can be repaired by recalibrating existing representations rather than learning new ones.

1 Introduction

LLMs are trained to refuse harmful instructions while answering harmless ones (Ouyang et al., 2022; Bai et al., 2022). Yet this behavior is uneven across languages: harmful prompts in lower-resource languages often succeed where equivalent English prompts are refused (Deng et al., 2024; Yong et al., 2023; Wang et al., 2024; Shen et al., 2024). Figure 1 illustrates this pattern, showing that refusal rates for harmful prompts drop sharply as language resources decrease, while harmless prompts remain largely unaffected. These failures are typically measured behaviorally, leaving their internal cause unclear.

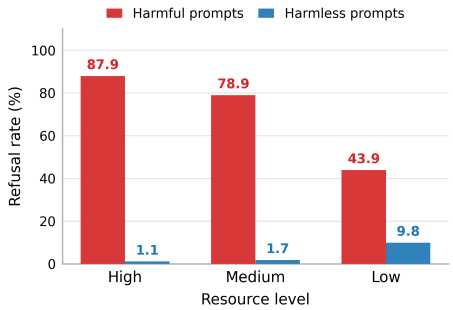

Figure 1: **Refusal degrades with lower language resource tier.** Macro refusal rates across Qwen2.5-7B-Instruct, Gemma-2-9B-it, and Llama-3.1-8B-Instruct show harmful refusal falling sharply in LRLs while harmless refusal stays low.

When a model answers a harmful low-resource request, two failures are observationally indistinguishable. The model may fail to recognize the request as harmful, or it may *recognize* it but fail to *act* on that recognition. Prior work has documented the behavioral gap and proposed mitigations that transfer a stronger safety signal from English or other high-resource languages (Zhang et al., 2025; Zhao et al., 2025c; Bu et al., 2026; Yang et al., 2026), but the underlying question has remained open: *do lower-resource prompts lack a usable harmfulness representation* (Wang et al., 2025; Verma and Bharadwaj, 2025), *or do they fail to use one that is already present?*

We diagnose this question in the residual stream. Recent work shows that refusal can be mediated by latent directions in activation space (Arditi et al., 2024; Wang et al., 2025). This gives us a falsifiable test. If low-resource failures reflect missing harmfulness representations, a direction learned from

high-resource activations should fail to separate harmful from harmless low-resource prompts. If the failures instead reflect routing, the same direction should remain discriminative even when the model fails to refuse.

Across a 23-language extension of PolyRefuse (Wang et al., 2025) and three instruction-tuned language models, the second hypothesis holds. Harmfulness remains linearly separable in low-resource activations, and a harmfulness direction extracted entirely from high-resource data still causally mediates refusal when steered. What shifts is the magnitude of the signal: low-resource prompts produce lower projections onto the harmfulness direction, so the same latent evidence less reliably triggers the model's implicit refusal threshold.

This diagnosis points to a simple intervention. We introduce a few-shot latent gate that reuses the high-resource harmfulness signal and recalibrates its decision threshold using a small number of target-language examples, avoiding the need to learn a new low-resource direction from many examples. The gate routes between refusal steering and harmfulness-direction ablation, improving selective refusal across most model-language pairs, transferring to out-of-distribution safety benchmarks, and preserving benign instruction following better than adapted steering baselines (Lee et al., 2025; Zhao et al., 2025b).

Our contributions can be summarized as follows:

- We show that low-resource refusal failures across 23 languages and three instruction-tuned models are not failures of harmfulness representation: harmfulness remains linearly separable in internal activations even when models fail to refuse.
- We localize the failure to the calibration of the safety decision. A harmfulness direction learned from high-resource languages remains both discriminative and causally effective in lower-resource languages, but its score distribution shifts so that the model's implicit refusal threshold no longer fires reliably.
- We propose a few-shot latent gate that resets the decision threshold with as few as 1 to 4 target-language examples per class, improving selective refusal and preserving benign instruction following better than adapted steering baselines under matched supervision.

2 Related Work

Multilingual Safety Gap. Prior work consistently shows that safety degrades in lower-resource languages (Deng et al., 2024; Yong et al., 2023; Wang et al., 2024; Shen et al., 2024; Yong et al., 2025): unsafe generations increase as language resources decrease, translated AdvBench prompts elicit harmful outputs (Yong et al., 2023), and non-English inputs yield more unsafe and irrelevant responses despite multilingual SFT and RLHF (Wang et al., 2024; Shen et al., 2024). However, these findings are based on response-level behavior and do not explain the underlying mechanism. It remains unclear whether models fail to separate harmful from harmless prompts, or separate them but fail to translate this signal into refusal. In this work, we study this distinction at the representation level.

Multilingual Safety Alignment. Existing methods for closing the multilingual safety gap typically strengthen safety behavior through additional training or auxiliary safety mechanisms. Approaches include reward-gap optimization (Zhao et al., 2025c), representation consistency objectives (Bu et al., 2026; Yang et al., 2026), sparse or language-specific weight edits (Liang et al., 2026; Banerjee et al., 2025), English-anchored multilingual alignment training (Zhang et al., 2025), and multilingual safety classifiers (Kumar et al., 2025; Verma et al., 2025). In this work, we take a complementary mechanistic approach. Rather than first adding new multilingual safety knowledge through weight updates or a separate text-level guard, we diagnose the gap in the residual stream and show that harmful–harmless information is already present in lower-resource activations. Our intervention then reuses this high-resource harmfulness signal and lightly recalibrates how it is routed into refusal, improving low-resource safety without updating model weights or training a new multilingual safety model.

Mechanistic Interpretability. LLMs often encode high-level concepts in latent directions (Zou et al., 2025; Ying et al., 2026; Lu et al., 2026). For refusal, Arditi et al. (2024) find a residual-stream direction whose removal suppresses refusal on harmful prompts and whose addition induces refusal on harmless prompts. Later work finds multi-dimensional refusal geometry (Wollschläger et al., 2025; Pan et al., 2025; Joad et al., 2026), separable harmfulness and refusal concepts (Lee

et al., 2025), and token-position effects (Zhao et al., 2025a). Multilingual interpretability also finds shared cross-lingual semantics (Wendler et al., 2024; Dumas et al., 2025; Wu et al., 2025), while Wang et al. (2025) show refusal directions transfer across safety-aligned languages. Wang et al. (2025); Verma and Bharadwaj (2025) posit that lower-resource safety gaps come from harmful–harmless overlap caused by weaker semantic understanding. We find this incomplete: lower-resource languages can encode nontrivial harmful–harmless separation that still fails to induce refusal.

3 Setup: Models, Data, and Harmfulness Directions

Languages and resource tiers. Because model-specific pretraining mixtures are usually unavailable, we use Common Crawl share as a proxy for resource level (Touvron et al., 2023; Penedo et al., 2023; Gao et al., 2020; Soldaini et al., 2024; Wenzek et al., 2020): above 1% for high-resource languages (HRLs), 0.1–1% for medium-resource languages (MRLs), and below 0.1% for low-resource languages (LRLs). The 10 HRLs are English, German, French, Spanish, Italian, Dutch, Polish, Russian, Chinese, and Japanese; the 7 MRLs are Arabic, Korean, Thai, Greek, Hebrew, Hindi, and Persian; and the 6 LRLs are Swahili, Amharic, Burmese, Khmer, Sinhala, and Yoruba.

Dataset. We extend[1] PolyRefuse (Wang et al., 2025) to 23 languages: 10 HRLs, 7 MRLs, and 6 LRLs. Each language has 260/39/572 harmful train/validation/test prompts and 200/200/500 harmless train/validation/test prompts. The train split is used for our calibration and adapted AdaSteer; CAST additionally uses validation for condition-layer and threshold tuning. The test split is solely used for evaluation.

Models and refusal scoring. The main experiments use Qwen2.5-7B-Instruct, gemma-2-9b-it, and Llama-3.1-8B-Instruct. We greedily decode harmful and harmless PolyRefuse prompts and use LLM-as-a-judge (Liu et al., 2023; Zheng et al., 2023) to label refusal. We chose GPT-4o-mini as the judge for its broad multilingual coverage and cost efficiency. To validate its robustnesss we also measured the pearson correlation between LLM and human judge labels, which was strong at 0.79 (Appendix F).

[1] see Appendix A for more details

Harmfulness directions. We use the standard contrastive-mean construction (Arditi et al., 2024; Wang et al., 2025) to extract a one-dimensional encoding of harmfulness from model activations. For a prompt x, let $h_k(x) \in \mathbb{R}^d$ denote the residual-stream activation (Elhage et al., 2021) at the final token of layer k. For each language ℓ, we average $h_k(x)$ separately over a balanced contrastive set of harmful prompts $\mathcal{D}_{\ell,H}$ and harmless prompts $\mathcal{D}_{\ell,N}$,

$$\mu_{\ell,s} = \frac{1}{|\mathcal{D}_{\ell,s}|} \sum_{x \in \mathcal{D}_{\ell,s}} h_k(x), \quad s \in \{H, N\},$$

and define the language-ℓ harmfulness direction as the ℓ_2-normalized difference of means:

$$v_\ell = \frac{\mu_{\ell,H} - \mu_{\ell,N}}{\|\mu_{\ell,H} - \mu_{\ell,N}\|_2}.$$

By construction, v_ℓ points from the harmless cluster toward the harmful cluster, so projections $s(x) = h_k(x)^\top v_\ell$ are higher for harmful prompts than harmless ones. We use v_ℓ both as a measurement tool and as an intervention target. As a measurement tool, we project activations onto it to test whether harmfulness is decodable. As an intervention target, we add or ablate it to test whether it causally mediates refusal.

4 Diagnosing the Multilingual Refusal Gap

This section asks where multilingual safety alignment breaks down. We first measure the behavioral gap across resource tiers, then test whether the harmfulness representation responsible for refusal in high-resource languages is still present in lower-resource ones, and how that representation relates to the model's refusal behavior.

Harmful refusal degrades with resource tier. We generate greedy completions for harmful and harmless PolyRefuse prompts, score them with the refusal judge, and report refusal rates by language. Because a low-resource gap could reflect broad instruction-following degradation, we measure harmful and harmless refusal separately. Figure 1 summarizes the result, with Appendix Table 3 giving the per-language breakdown. Averaged across model families, harmful refusal falls from 87.9% in HRLs to 78.9% in MRLs and 43.9% in LRLs. The pattern holds by model: Qwen drops from 85.6% to 28.8%, Llama from 83.5% to 32.5%, and the stronger Gemma-2-9B from

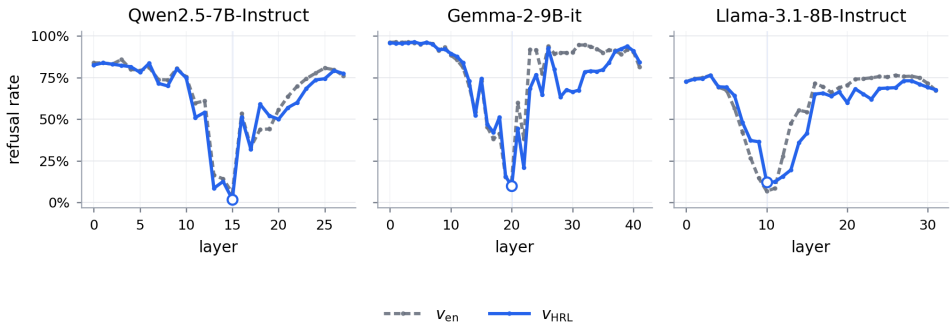

Figure 2: **Harmful directions mediate refusal in middle layers.** Directional ablations show that HRL harmfulness directions encode harmful refusal on tested HRL PolyRefuse prompts, peaking at layer 15 for Qwen, 20 for Gemma, and 10 for Llama.

94.5% to 70.3%. Harmless refusal stays much lower throughout, with an aggregate LRL average of 9.8%. The failure is therefore selective: models often answer harmful low-resource requests while still answering harmless ones. We call this the *Multilingual Refusal Gap* and ask whether it reflects a missing harmfulness representation or a failure to act on one that is present.

A high-resource direction causally mediates refusal. We test whether refusal is mediated by a residual-stream direction. Following Arditi et al. (2024), we ablate a candidate direction v from the residual stream across all token positions, including during autoregressive generation:

$$h_k(x) \leftarrow h_k(x) - v_\ell {v_\ell}^T h_k(x)$$

If v_ℓ mediates refusal, removing it at layer k should reduce harmful refusal. We therefore ablate v_{HRL}, the direction from pooled activations of the 10 HRLs, at each layer and compare it to the English-derived baseline v_{en} (Arditi et al., 2024).

Figure 2 shows that v_{HRL} drives harmful refusal close to zero in Qwen2.5-7B and below 15% in Gemma-2-9B and Llama-3.1-8B at middle layers, while refusal stays much higher outside this band. The pooled HRL direction also outperforms v_{en} in Qwen and Gemma and matches it in Llama. We define each model's *extraction layer* as the layer where ablating v_{HRL} most reduces harmful refusal: layer 15 for Qwen, 20 for Gemma, and 10 for Llama. Subsequent analyses use v_{HRL} at these layers.

At the extraction layer, projections $s(x) = h_k(x)^\top v_{\text{HRL}}$ also separate harmful from harmless prompts (Figure 3; Appendix Figure 19). Combined with the ablation result, this establishes v_{HRL} as both a causal mediator of refusal and a linear predictor of harmfulness.

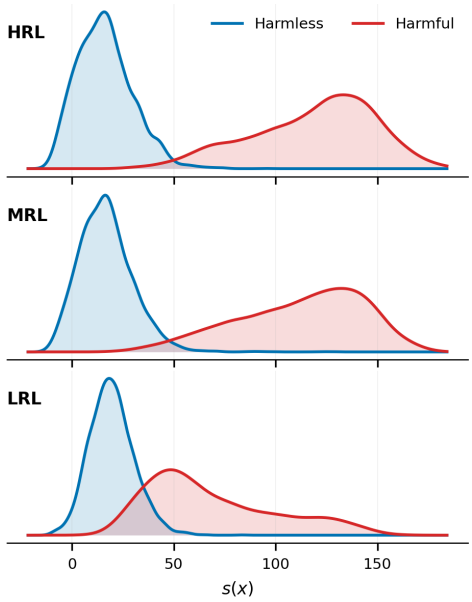

Figure 3: **Lower-resource prompts shift harmfulness-score distributions.** Gemma-2-9B projections on v_{HRL} show harmful and harmless $s(x)$ distributions within each resource tier; harmful projections shift downward most clearly in the LRL panel.

The harmfulness signal is preserved in lower-resource languages. Prior work attributes the lower-resource refusal gap to weaker safety representations or understanding (Wang et al., 2025; Verma and Bharadwaj, 2025). We test this directly by projecting LRL and MRL activations onto v_{HRL} and measuring how well the resulting scores separate harmful from harmless prompts. Figure 5 reports test AUC across all 23 languages: even the weakest LRL cells remain far above chance, with most languages above 0.85. The outlined cells make the dissociation explicit: high decodability does not yield high refusal. The harmfulness sig-

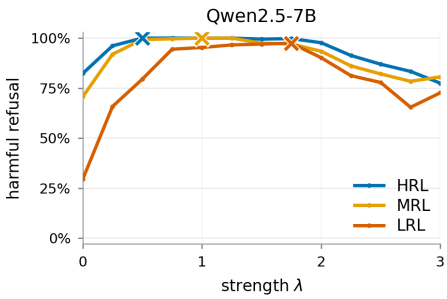

Figure 4: **Adding the HRL direction can recover refusal, but the needed amount differs by tier.** Curves average Qwen2.5-7B harmful refusal within each resource tier after adding λv_{HRL}. Crosses mark tier-wise peaks.

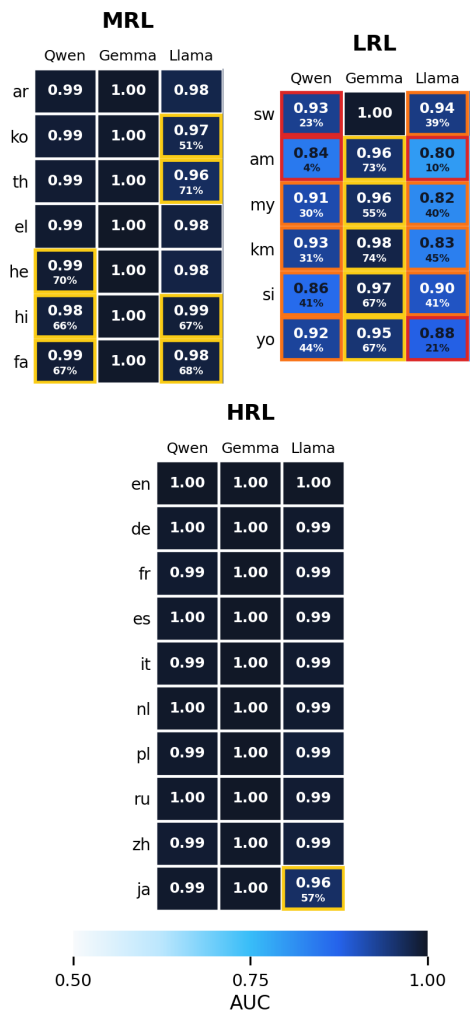

Figure 5: **Harmfulness remains decodable even when models fail to refuse.** Cells report PolyRefuse test AUC from $s(x)$ under the pooled HRL direction. Yellow, orange, and red borders mark harmful-refusal rates of 50–75%, 25–50%, and below 25%, respectively. In highlighted cells, smaller numbers are actual harmful-refusal rates.

nal is present in low-resource activations along the same direction that mediates HRL refusal, but the model fails to act on it.

Low-resource projections are smaller in magnitude. What changes in low-resource languages is not the presence of the signal but its scale. Figure 3 shows Gemma's $s(x)$ distributions within each resource tier: in the aggregated LRL panel, harmful and harmless prompts remain separable, but the mean harmful score shifts downward. Qwen and Llama shows the same pattern (Figure 19). We test whether this magnitude shift explains the refusal failure by steering along v_{HRL} with increasing strength:

$$h_k(x) \leftarrow h_k(x) + \lambda \cdot v_{\text{HRL}}, \lambda \in \{0, 0.25, 0.5, \ldots, 3\}.$$

Figure 4 shows that adding v_{HRL} recovers LRL refusal, but lower-resource tiers need larger λ to reach peak refusal than HRLs do. The harmfulness direction remains behaviorally usable in low-resource languages; what is shifted is the amount of activation needed to route it into refusal. The remaining sections build on this diagnosis: the representation is intact, so the right intervention is to recalibrate how it is used, not to relearn it.

5 A Few-Shot Latent Gate for Calibration and Routing

5.1 Calibrating a Few-Shot Latent Gate

If low-resource harmfulness is present but shifted, the next question is whether it can be used with only minimal target-language supervision. We therefore test whether an HRL-aligned harmfulness readout becomes a reliable LRL safety gate after seeing just a few harmful and harmless examples.

Few-shot threshold calibration. A latent gate maps a scalar harmfulness readout to a binary safety decision via a learned threshold. Direction readouts use $s(x) = h_k(x)^\top v$; subspace readouts first project $h_k(x)$, then train logistic regression on the projected coordinates (Algorithm 1), using the pre-sigmoid logit as $s(x)$. For each budget and LRL, we choose the threshold τ_ℓ that maximizes F1 on b harmful and b harmless training examples. When $b = 0$, we calibrate on HRL training data. Thresholds are frozen before held-out LRL evaluation, and test F1 is averaged across LRLs. All experiments in this section were repeated on 10 seeds.

The HRL direction is already a strong few-shot gate. Figure 6 compares fixed v_{HRL} against a target-language direction v_{LRL} estimated from the same examples. Zero-shot HRL thresholds can be

Figure 6: **A few target-language examples recover LRL harmfulness gates.** Each curve reports macro LRL test F1 after choosing a language-specific binary threshold with b harmful and b harmless target-language examples. The random-direction curve is a one-dimensional control whose threshold is calibrated with the same target-language examples.

Algorithm 1 Training the HRL harmfulness subspace gate

Require: Layer-k activations $h_k(\cdot)$, rank r, target-language budget b
Step 1: Compute per-language harmfulness directions.
$\mu_{\ell,H}, \mu_{\ell,N}$: mean activations of harmful (H) and harmless (N) prompts in language ℓ.
for each source HRL ℓ **do**
  $d_\ell \leftarrow \text{normalize}\big(\mu_{\ell,H}^{\text{train}} - \mu_{\ell,N}^{\text{train}}\big)$
end for
Step 2: Build rank-r subspace from pooled HRL directions.
$B_r \leftarrow$ top r right-singular vectors of row stack $[d_\ell]_{\ell \in \text{HRL}}$
$z(x) \leftarrow h_k(x)^\top B_r$ ▷ subspace features
Step 3: Assemble training set $\mathcal{T}$.
if $b > 0$ **then**
  Sample b harmful and b harmless target-language examples
  $\mathcal{T} \leftarrow$ HRL train examples $\cup$ sampled target examples
else
  $\mathcal{T} \leftarrow$ HRL train examples
end if
Standardize $z(x)$ using statistics from $\mathcal{T}$
Step 4: Fit gate and select threshold.
Fit logistic readout $g(z) = w^\top z + c$ on $\mathcal{T}$ (L2-regularized, balanced cross-entropy)
Select threshold τ on training logits ($\mathcal{T}$)
Freeze B_r, g, and the threshold; evaluate harmfulness-gate F1 on the target test split

poorly placed, especially for Qwen and Llama, but one or two target-language examples per class often move them into a useful range. Thus v_{HRL} is more sample-efficient than estimating v_{LRL} from scratch: local directions improve with more labels, but at small budgets are usually worse than LRL-specific calibration of the HRL direction. The low-resource signal is aligned enough to use; its operating point is shifted.

Simple latent gates are competitive with higher-capacity guards. The same pattern (Figure 6) holds against higher-capacity OMNIGuard fine-tuning (Verma et al., 2025). To match source data, OMNIGuard is trained on HRLs and fine-tuned separately for each LRL with the same b examples per class. It improves with target-language examples, but even against the higher-capacity OMNIGuard baseline, the lightweight latent gates remain competitive or stronger, especially for Qwen.

A shared HRL subspace improves the gate. We also replace the single HRL direction with a rank-10 harmfulness subspace fit from HRL training languages (Algorithm 1). The subspace is still HRL-only before calibration, but it captures multiple HRL harmfulness axes, allowing the gate to use more than one high-resource direction. Against a random-direction control calibrated with the same examples, the learned HRL subspace ((Figure 6)) wins at every nonzero budget for all three models, with the largest gap for Gemma. The gain therefore reflects harmfulness-aligned geometry beyond threshold calibration.

Latent gates generalize beyond the calibration distribution. Figure 7 evaluates the Gemma gates on two out-of-distribution safety benchmarks: MultiJail (Deng et al., 2024) and IndoSafety (Azmi et al., 2025). We test the transfer without calibrating on OOD (Zero-shot) and with a single calibration example (One-shot). Transfer beyond PolyRefuse is strong: the best Gemma gate reaches $0.933/0.902$ balanced accuracy on MultiJail/IndoSafety. The full all-model results in Figure 10 show the same broad pattern for Qwen and a different one for Llama. For Qwen and Gemma, one-shot v_{HRL} is strongest; for Llama, the subspace gate improves from 0.653 to 0.765 on MultiJail and 0.560 to 0.713 on IndoSafety.

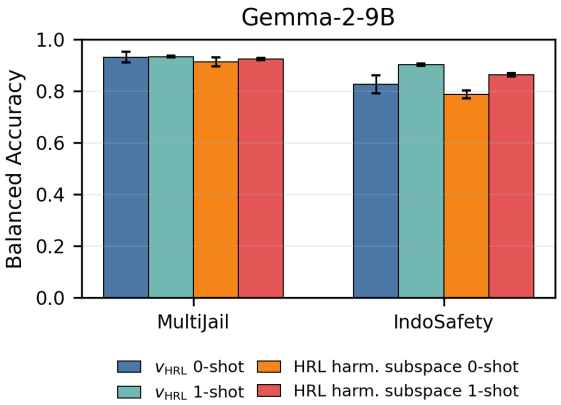

Figure 7: **Gemma few-shot latent gates on out-of-distribution safety benchmarks.** Bars report held-out balanced accuracy on MultiJail and IndoSafety for Gemma-2-9B, averaged within each dataset family. Error bars show the standard error across target languages and calibration seeds.

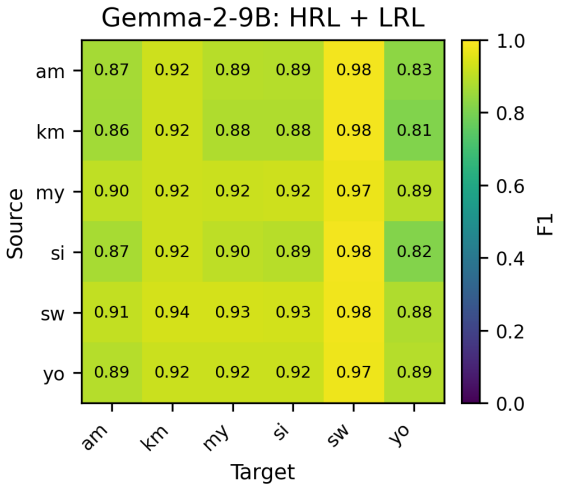

Figure 8: **Gemma LRL calibration often transfers across source–target pairs.** Cells report test F1 for an HRL subspace gate trained with HRL data plus the source LRL and evaluated on the target LRL. Diagonal cells report held-out same-language F1.

LRL calibration transfers beyond one language. Figure 8 asks whether adding one LRL to the HRL subspace gate helps on other LRLs. Calibration often transfers for Gemma: diagonal and off-diagonal means nearly match (0.912 vs. 0.908). The all-model matrix in Figure 11 shows that Qwen has a smaller but useful pattern (0.843 vs. 0.792). The diagonal is not always strongest; in several cases, a gate calibrated on one LRL works better on other LRLs than on that language's own held-out examples. This suggests few-shot examples can expose a reusable harmfulness subspace whose transfer depends more on target distribution than source–target language match. Llama is the caveat, with a larger diagonal–off-diagonal gap (0.804 vs. 0.628) and more uneven transfer.

5.2 Routing the Calibrated Gate into Refusal

We now synthesize the diagnostics into a training-free steering method, evaluated on the six PolyRefuse LRLs where the refusal gap is largest. Baselines[2] are state-of-the-art latent steering methods, CAST and AdaSteer.

Algorithm 2 Conditional HRL refusal intervention

Require: Activation $h_k(x)$, gate logit $g(x)$, threshold τ, Unit direction $\hat{v}_{\text{HRL}}$
$S_{\text{HRL},c} \leftarrow \{h_k(x)^\top \hat{v}_{\text{HRL}} : x \in \mathcal{D}^{\text{train}}_{\text{HRL},c}\}, c \in \{H, N\}$
$\lambda \leftarrow Q_{0.75}(S_{\text{HRL},H}) - Q_{0.25}(S_{\text{HRL},N})$ ▷ interquartile score range
if $g(x) > \tau$ **then**
  $h_k(x) \leftarrow h_k(x) + \lambda\, \hat{v}_{\text{HRL}}$
else
  $h_k(x) \leftarrow h_k(x) - \hat{v}_{\text{HRL}} \hat{v}^T_{\text{HRL}} h_k(x)$
end if

Conditional steering. Following CAST (Lee et al., 2025), we route between refusal steering and directional ablation at the extraction layer. Prompts classified as harmful receive refusal steering; prompts classified as harmless have the HRL harmfulness direction removed, improving harmful refusal while preserving benign instruction following. Algorithm 2 gives the intervention, where g is the subspace gate from Algorithm 1 and τ is calibrated on the same data. We set λ as the gap between HRL harmful upper-quartile and harmless lower-quartile projection scores. This moves low-resource harmful activations toward the high-resource harmful score regime **without tuning** a language-specific steering strength.

Experimental setup. We train or calibrate each method with matched data: **Original** uses each prior method's released training data; **HRL** uses 200 PolyRefuse HRL examples per language and class; **HRL + 32 LRL** adds 32 target-language LRL examples per class.

Zero-shot HRL routing is strong. Table 1 shows that an HRL harmfulness subspace can be routed into refusal without target-language calibration. With HRL data only (Zero-shot), our method raises mean Δ from 15.3 to 38.6 on Qwen and 60.1 to 75.6 on Gemma. The gain is selective: averaged across model–language pairs, zero-shot HRL routing reaches 54.5% harmful refusal with 10.1% harmless refusal, while CAST (Original)

[2]see Appendix C for more details

Model / Method	sw			am			my			km			si			yo		
	Harm.↑	Harml.↓	Δ ↑	Harm.↑	Harml.↓	Δ ↑	Harm.↑	Harml.↓	Δ ↑	Harm.↑	Harml.↓	Δ ↑	Harm.↑	Harml.↓	Δ ↑	Harm.↑	Harml.↓	Δ ↑
Qwen2.5-7B-Instruct	22.9	9.0	13.9	4.4	**5.4**	-1.0	29.5	8.4	21.1	31.1	7.0	24.1	41.4	**11.6**	29.8	43.5	39.8	3.7
+ Ours (HRL)	**56.6**	10.6	46.0	23.3	6.2	17.1	46.0	**7.8**	38.2	55.6	8.6	47.0	61.2	16.8	44.4	**87.6**	48.4	**39.2**
+ Ours (HRL + 32 LRL)	**56.6**	10.4	**46.2**	32.2	10.4	**21.8**	51.0	10.8	**40.2**	74.3	15.6	**58.7**	**74.7**	25.6	**49.1**	87.2	48.6	38.6
+ CAST (Original)	29.2	12.8	16.4	10.3	10.2	0.1	37.1	10.4	26.7	43.4	13.0	30.4	48.4	17.4	31.0	46.9	**36.2**	10.7
+ CAST (HRL + 32 LRL)	21.0	**7.0**	14.0	6.1	6.0	0.1	30.9	8.4	22.5	29.2	**5.8**	23.4	36.4	13.4	23.0	50.0	40.8	9.2
+ AdaSteer (Original)	43.5	25.8	17.7	**71.9**	81.6	-9.7	**82.0**	66.2	15.8	**79.9**	53.0	26.9	73.3	53.8	19.5	79.2	77.2	2.0
+ AdaSteer (HRL + 32 LRL)	26.7	16.4	10.3	9.3	20.6	-11.3	38.1	18.6	19.5	40.7	13.2	27.5	45.6	20.6	25.0	44.8	47.8	-3.0
Gemma-2-9B	86.2	**1.0**	85.2	72.7	14.4	58.3	54.9	**3.8**	51.1	74.3	**5.4**	68.9	67.0	5.8	61.2	66.6	30.4	36.2
+ Ours (HRL)	95.5	3.8	91.7	84.3	**12.6**	71.7	81.6	4.4	77.2	86.2	6.4	79.8	81.8	**5.2**	76.6	76.2	**19.6**	56.6
+ Ours (HRL + 32 LRL)	**96.7**	3.6	**93.1**	**91.6**	16.4	**75.2**	**85.1**	5.8	**79.3**	**90.9**	8.2	**82.7**	**90.2**	8.0	**82.2**	**90.4**	25.6	**64.8**
+ CAST (Original)	87.6	**1.0**	86.6	77.6	18.0	59.6	55.6	4.4	51.2	79.2	6.0	73.2	75.2	8.4	66.8	73.3	33.6	39.7
+ CAST (HRL + 32 LRL)	88.3	**1.0**	87.3	74.3	15.8	58.5	55.4	4.2	51.2	81.1	6.0	75.1	72.2	8.6	63.6	73.6	31.4	42.2
+ AdaSteer (Original)	86.4	4.0	82.4	70.5	29.6	40.9	50.7	14.6	36.1	74.0	17.0	57.0	57.3	16.8	40.5	70.5	39.4	31.1
+ AdaSteer (HRL + 32 LRL)	73.3	9.4	63.9	40.0	72.4	-32.4	48.1	38.4	9.7	63.3	49.6	13.7	47.0	45.6	1.4	62.4	72.0	-9.6
Llama-3.1-8B-Instruct	38.6	**0.8**	37.8	9.8	7.0	2.8	40.2	8.0	32.2	44.8	5.2	39.6	40.9	4.8	36.1	20.8	9.8	11.0
+ Ours (HRL)	29.0	1.0	28.0	8.9	**6.0**	2.9	33.4	7.6	25.8	25.3	**3.6**	21.7	31.3	**4.6**	26.7	17.7	**8.6**	9.1
+ Ours (HRL + 32 LRL)	53.7	1.4	**52.3**	32.3	8.4	**23.9**	46.7	**7.2**	**39.5**	58.2	4.8	**53.4**	64.2	8.0	**56.2**	32.7	9.2	**23.5**
+ CAST (Original)	50.0	37.6	12.4	58.9	53.0	5.9	77.6	57.4	20.2	70.6	58.0	12.6	**88.5**	80.6	7.9	76.4	72.4	4.0
+ CAST (HRL + 32 LRL)	45.1	10.4	34.7	26.4	18.8	7.6	54.5	26.4	28.1	53.1	23.6	29.5	81.1	57.2	23.9	54.7	43.8	10.9
+ AdaSteer (Original)	46.2	5.0	41.2	16.8	15.0	1.8	51.6	17.4	34.2	55.8	13.6	42.2	58.2	22.2	36.0	28.3	15.4	12.9
+ AdaSteer (HRL + 32 LRL)	**83.4**	79.2	4.2	**93.2**	84.2	9.0	**91.3**	92.2	-0.9	**87.2**	87.8	-0.6	86.0	92.2	-6.2	**91.8**	89.6	2.2

Table 1: Low-resource test refusal rates by steering method: harmful-refusal, harmless-refusal, and Δ (harmful minus harmless) percentages. Ours (HRL) uses only the HRL-fitted rank-10 conditional v_{HRL} subspace; Ours (HRL + 32 LRL) adds 32 harmful and 32 harmless target-language calibration examples. CAST (Original) and AdaSteer (Original) use each method's own released training data. Bold marks the best value and underline marks the second-best value within each model, language, and metric.

Model	sw	am	si	yo	Avg. Δ
Qwen2.5-7B	26.9→27.8	26.2→26.2	28.0→28.2	27.9→28.4	+0.4
Gemma-2-9B	28.9→30.1	23.1→23.2	27.7→28.9	23.0→23.0	+0.6
Llama-3.1-8B	34.5→34.4	30.3→30.8	33.4→33.1	25.3→25.3	+0.0

Table 2: **Utility is preserved after steering.** Global-MMLU accuracy (%) before and after *Ours (HRL + 32 LRL)* conditional steering.

and AdaSteer (Original) reach higher harmful refusal but much higher harmless refusal (29.5% and 31.5%). Llama is the exception, where the HRL-only gate underperforms the base model, matching the earlier finding that shared HRL readouts are not automatically calibrated for every model and language.

A small LRL budget closes most gaps. Adding 32 harmful and 32 harmless target-language examples improves Δ in 17 of 18 model–language pairs. The gain is largest for Llama, where mean Δ moves from 19.0 with HRL-only routing to 41.5 with HRL + 32 LRL; Qwen and Gemma improve from 38.6 to 42.4 and 75.6 to 79.6. These results show that we can efficiently calibrate the harmfulness readout without relearning a new latent direction.

Our method is most selective. HRL + 32 LRL achieves the best Δ in 17 of 18 pairs, reaching 54.5 mean Δ, substantially above the strongest adapted baseline, CAST (HRL + 32 LRL) at 33.6. CAST keeps harmless refusal low (18.3%) but only reaches 51.9% harmful refusal; our method lowers harmless refusal to 12.7% while raising harmful refusal to 67.2%. Utility is preserved on multilingual MMLU, with minor gains for Qwen and Gemma (Table 2). AdaSteer under the same HRL + 32 LRL setup over-refuses benign prompts, averaging 52.8% harmless refusal and only 6.8 mean Δ.

6 Conclusion and Discussion

Conclusion Low-resource safety failures are not failures to represent harmfulness. Across the models and languages we test, harmfulness remains linearly separable, causally tied to refusal, and behaviorally recoverable through steering. What fails is the calibration that turns this signal into a refusal decision, and a few-shot latent gate can fix it: by resetting only the decision threshold on a handful of target-language examples, it improves selective refusal across most model–language pairs while preserving benign instruction following better than adapted steering baselines.

Implications. Behavioral refusal rates alone conflate two distinct failure modes: a model that lacks a harmfulness representation in a given language, and a model that has one but fails to act on it. Our results show these can come apart, and that current low-resource refusal gaps in the studied models reflect the second case more than the first. The two failures call for different fixes: missing representations call for better representation learning, while weakly routed ones can be repaired with small target-language calibration. The practical path is a diagnostic-then-fix workflow: test whether harmfulness is represented before deciding how to repair its use.

Limitations

Scope. We study three open dense instruction-tuned 7B–9B models and 23 PolyRefuse languages; frontier, MoE/sparse models and other languages may use different mechanisms, and Common Crawl share is a coarse resource proxy.

Evaluation and access. We score greedy completions with GPT-4o-mini, so automatic judgments can miss multilingual nuance; interventions require activation access and are diagnostics, not closed-model safeguards.

Training coverage. Gated steering calibrates when to refuse; it does not replace multilingual safety training or guarantee refusal wording, harmful-category coverage, or adversarial-prompt robustness.

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A Dataset Details

A.1 PolyRefuse

PolyRefuse is the main safety dataset in our experiments. Its harmful prompts come from AdvBench (Zou et al., 2023), MaliciousInstruct (Huang et al., 2024), and TDC2023 (Mazeika et al., 2023); its harmless prompts come from Alpaca (Taori et al., 2023). The original release google translates these English prompts into 13 non-English languages (Wang et al., 2025). We keep those languages and add Greek, Hebrew, Hindi, Persian, Swahili, Amharic, Burmese, Khmer, and Sinhala using Google Translate. We measure translation quality using SBERT (Reimers and Gurevych, 2019) and find that the translation preserves semantic meaning after back-translation (Table 4).

We evaluate 23 languages. English, German, French, Spanish, Italian, Dutch, Polish, Russian, Chinese, and Japanese form the HRL tier; Arabic, Korean, Thai, Greek, Hebrew, Hindi, and Persian form the MRL tier; Swahili, Amharic, Burmese, Khmer, Sinhala, and Yoruba form the LRL tier. Tiers follow Common Crawl share: HRL above 1%, MRL between 0.1% and 1%, and LRL below 0.1%. Each language has 260/39/572 harmful train/validation/test prompts and 200/200/500 harmless train/-validation/test prompts. Table 5 summarizes the language-family coverage of the extension.

A.2 Global-MMLU

Global-MMLU (Singh et al., 2025) is our utility benchmark. It extends MMLU for 42 languages using professional translations, crowdsourced translations, machine translations, human quality review, and post-edits. It also marks questions that depend on cultural, geographic, or dialect knowledge. We use it only for Table 2.

Global-MMLU overlaps with four of our six LRLs: Amharic, Sinhala, Swahili, and Yoruba. Burmese and Khmer are missing, so the Global-MMLU utility table covers the four overlapping languages.

A.3 IndoSafety

IndoSafety (Azmi et al., 2025) is a culturally grounded safety benchmark for formal Indonesian, colloquial Indonesian, Javanese, Sundanese, and Minangkabau. The benchmark extends beyond translated English harmful prompts by adding Indonesian-specific risks such as religious and ethnic sensitivities, regional separatism, Pancasila misinterpretation, Indonesian public entities, local cultural practices, and supernatural claims.

The dataset is human-verified and culturally localized. The formal Indonesian set includes translated and manually edited safety prompts, plus Indonesian-specific prompts written and checked by native speakers with local cultural and safety expertise. For the colloquial and local-language extension, the authors start with Google Translate for Javanese, Sundanese, and Minangkabau and GPT-4o for colloquial Indonesian, then have native speakers review and edit the outputs.

A.4 MultiJail

MultiJail (Deng et al., 2024) provides multilingual jailbreak prompts. It starts from 315 English unsafe prompts and adds native-speaker translations into Chinese, Italian, Vietnamese, Arabic, Korean, Thai, Bengali, Swahili, and Javanese. The original benchmark tests both direct multilingual prompts and prompts paired with an English jailbreak instruction. We only make use of the harmful multilingual prompts.

B Decoding Parameters

Completions use each model's chat template and greedy decoding. We generate at most 128 new tokens, disable sampling, and use no custom stop strings. The refusal judge is run deterministically as well through OpenRouter.

C Baseline Method Details

Baseline comparisons use released artifacts when available. The HRL variants train on the ten PolyRefuse HRLs, and the HRL + 32 LRL variants add 32 harmful and 32 harmless examples from the target LRL.

CAST. Conditional Activation Steering (CAST) (Lee et al., 2025) learns a condition vector and a behavior vector, then steers when the condition score (computed via cosine similarity) crosses a threshold. Our adapted version keeps this rule and estimates both directions from PolyRefuse contrastive activations. The condition layer and threshold are selected on held-out PolyRefuse data.

AdaSteer. AdaSteer (Zhao et al., 2025b) combines a Rejection Direction (RD) and a Harmfulness Direction (HD). Its steering coefficients are prompt-dependent and are computed from the final prompt-token residual. We use released vectors

Tier	Language	Qwen2.5-7B-Instruct		Gemma-2-9B-it		Llama-3.1-8B-Instruct	
		Harmful↑	Harmless↓	Harmful↑	Harmless↓	Harmful↑	Harmless↓
HIGH	English (en)	89.5	0.4	97.9	2.0	92.7	0.4
	German (de)	87.2	1.0	95.5	1.2	81.3	0.2
	French (fr)	85.1	1.0	95.3	1.6	90.7	0.6
	Spanish (es)	85.7	1.2	94.2	1.4	87.9	0.4
	Italian (it)	87.2	1.2	95.6	1.4	87.4	0.6
	Dutch (nl)	85.3	1.0	95.3	1.0	88.3	1.2
	Polish (pl)	87.6	0.8	94.9	1.8	80.6	0.4
	Russian (ru)	86.4	0.8	94.2	2.0	86.9	0.8
	Chinese (zh)	81.3	0.4	92.1	2.0	82.0	0.6
	Japanese (ja)	80.8	0.8	89.7	2.4	57.0	0.6
	Average	*85.6*	*0.9*	*94.5*	*1.7*	*83.5*	*0.6*
MEDIUM	Arabic (ar)	82.5	1.0	93.5	2.8	79.7	1.8
	Korean (ko)	77.3	1.4	88.3	1.6	50.5	0.0
	Thai (th)	81.5	1.2	92.8	2.4	71.3	1.6
	Greek (el)	76.6	5.2	94.4	0.4	75.2	0.4
	Hebrew (he)	69.6	3.4	93.5	0.8	76.6	1.8
	Hindi (hi)	66.3	3.4	92.7	1.4	67.0	1.2
	Persian (fa)	67.0	2.0	92.3	1.6	68.0	0.8
	Average	*74.4*	*2.5*	*92.5*	*1.6*	*69.8*	*1.1*
LOW	Swahili (sw)	22.9	9.0	86.2	1.0	38.6	0.8
	Amharic (am)	4.4	5.4	72.7	14.4	9.8	7.0
	Burmese (my)	29.5	8.4	54.9	3.8	40.2	8.0
	Khmer (km)	31.1	7.0	74.3	5.4	44.8	5.2
	Sinhala (si)	41.4	11.6	67.0	5.8	40.9	4.8
	Yoruba (yo)	43.5	39.8	66.6	30.4	20.8	9.8
	Average	*28.8*	*13.5*	*70.3*	*10.1*	*32.5*	*5.9*

Table 3: Refusal rates (%) by language and resource tier.

High-resource languages

Subset	de	fr	es	it	nl	pl	ru	zh	ja
Harmful	95.21	96.19	96.11	96.39	96.38	93.71	94.83	93.55	93.22
Harmless	96.51	97.53	97.68	97.59	97.73	93.83	95.96	95.45	95.51

Mid-resource languages

Subset	ar	ko	th	el	he	hi	fa
Harmful	95.13	92.73	90.31	95.98	95.97	95.91	94.54
Harmless	96.05	94.86	93.25	96.56	96.91	96.46	94.71

Low-resource languages

Subset	sw	am	my	km	si	yo
Harmful	92.41	92.14	91.76	88.05	94.47	91.81
Harmless	94.15	94.40	94.29	91.52	96.17	93.15

Table 4: SBERT back-translation similarity on PolyRefuse across train, validation, and test splits. Target-language prompts are back-translated to English and compared with the original English prompts; scores are cosine similarities scaled to 0–100.

Language family	Languages	Count
Indo-European	English, German, French, Spanish, Italian, Dutch, Polish, Russian, Greek, Hindi, Persian, Sinhala	12
Afro-Asiatic	Arabic, Hebrew, Amharic	3
Sino-Tibetan	Chinese, Burmese	2
Niger-Congo	Swahili, Yoruba	2
Japonic	Japanese	1
Koreanic	Korean	1
Kra-Dai	Thai	1
Austroasiatic	Khmer	1

Table 5: Language-family coverage in the 23-language PolyRefuse extension.

when available; otherwise we estimate RD and HD from the same PolyRefuse budget used by the other adapted baselines.

OMNIGuard / MultiGuard. OMNIGuard, released as MultiGuard (Verma et al., 2025), chooses a layer with a Universality Score (U-Score) and trains a harmfulness classifier on mean-pooled prompt representations. We compute U-Score on English-to-HRL translation pairs and train the classifier on PolyRefuse HRLs. With nonzero LRL budgets, we fine-tune the classifier on the same target examples used by the other adapted baselines.

D Out-of-Distribution Transfer Setup

The OOD transfer experiment keeps the gate fixed and changes the harmful prompt distribution. Harmful prompts come from MultiJail or IndoSafety (Appendix A.4; Appendix A.3).

Harmful prompts. MultiJail contributes harmful-only multilingual jailbreak prompts. IndoSafety contributes Indonesian and Indonesian-family harmful prompts with risk-area and harm-type metadata. We use the provided formal-Indonesian split and test-only splits for the regional-language cells.

Harmless prompts. The OOD benchmarks do not provide matched harmless prompts, so we pair their harmful examples with PolyRefuse harmless examples in the same language. For languages outside the PolyRefuse harmless set, we translate the English harmless splits. This changes the harmful side while keeping the harmless side comparable to the main task.

Gate evaluation. OOD gates use the same extraction layers as the main experiments. The zero-shot v_{HRL} gate keeps the HRL threshold. The one-shot setting chooses a balanced threshold from one harmful and one harmless target-language example. The HRL subspace gate uses the rank-10 readout in Algorithm 1. Figure 9 shows the per-language OOD transfer results. IndoSafety category plots fix the harmless side and vary only the harmful risk area or harm type.

E OOD Category Breakdown

Figure 12 shows where OOD transfer still fails by IndoSafety risk area. Qwen and Gemma remain strong across most categories. Llama improves with the HRL subspace gate but remains weaker. Information Hazards are the hardest risk area across models; direct Malicious Uses are easier for the same gates.

Figure 13 gives the same breakdown at the harm-type level. Privacy leakage, false or misleading information, and chatbot overreliance account for most of the drop. These prompts are less lexically direct than many weapon or illegal-action requests, making a single harmfulness threshold less stable under OOD transfer.

F Human Validation of the Refusal Judge

We manually check the GPT-4o-mini labels on sampled LRL test completions. Human validation focuses on LRLs because this is where automatic refusal judgments are expected to be least reliable and where our main empirical claims are concentrated. We sample 100 harmful + 100 harmless prompt-response pairs from each of the 3 models we study covering the 6 LRLs. Annotators see the original prompt and response, the parallel English PolyRefuse prompt, and a machine-translated English response, then mark whether the model refused. Figure 14 shows the resulting confusion matrix.

G Subspace Rank Sweep

For the HRL-only subspace gate, we sweep low ranks and calibration budgets from 0 to 64 examples per class. Rank 10 gives the best aggregate score; rank 8 is close for Gemma and several low-budget cells. Algorithm 1 gives the training procedure, Table 7 summarizes mean macro-LRL F1, and Figures 15–18 show the aggregate and per-language sweeps.
Figure 19 extends the tier-score diagnostic to Qwen and Llama, and Figure 20 reports the corresponding refusal-direction activation sweeps.

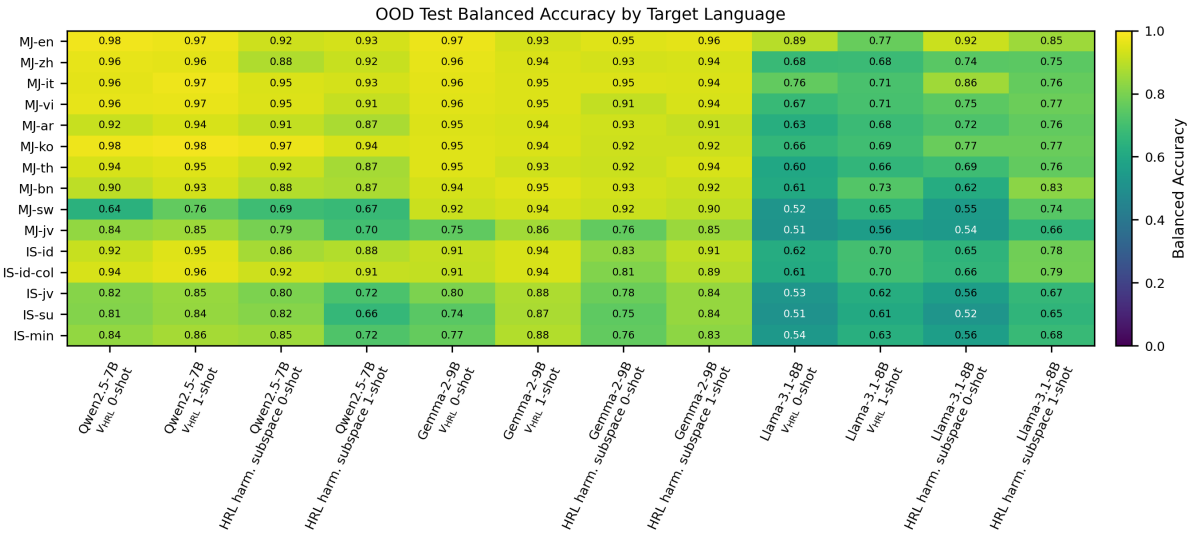

Figure 9: **OOD transfer by target language.** One-shot v_{HRL} is strongest for Qwen and Gemma; Llama gains more from the HRL subspace gate.

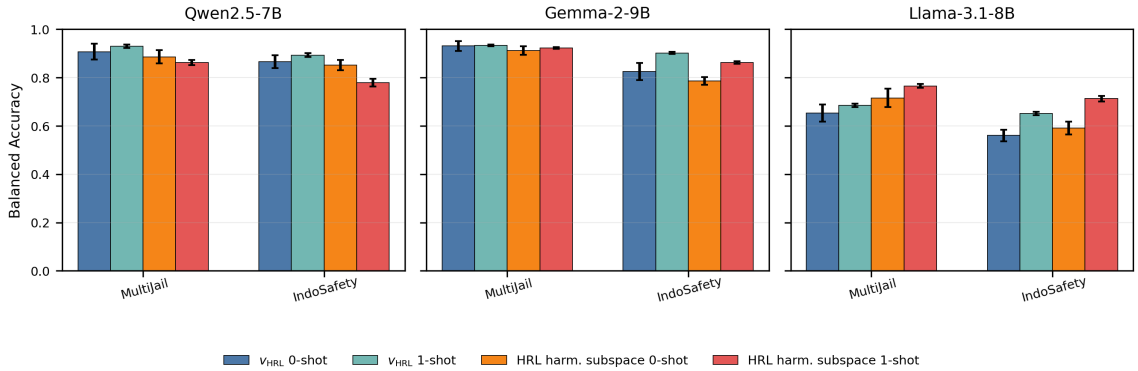

Figure 10: **All-model OOD transfer by dataset.** Full version of Figure 7, with Qwen2.5-7B, Gemma-2-9B, and Llama-3.1-8B.

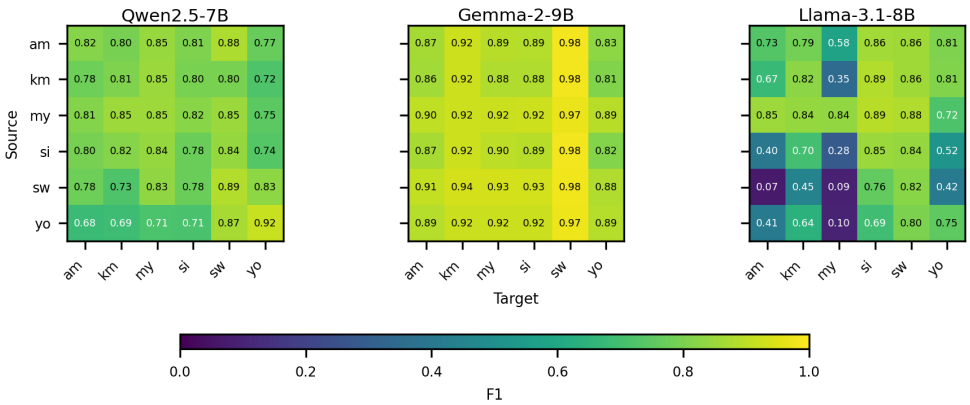

Figure 11: **All-model LRL calibration transfer across source–target pairs.** Full version of Figure 8, with one panel per model.

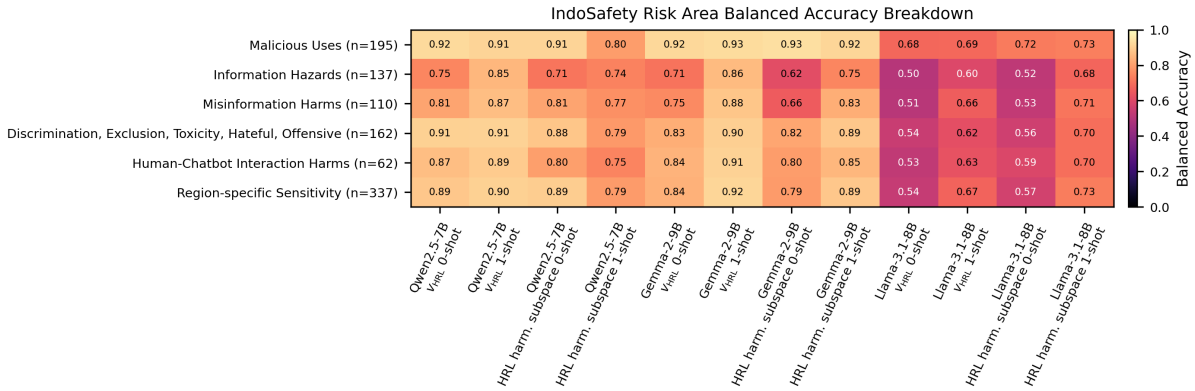

Figure 12: **IndoSafety risk areas.** Information Hazards are the weakest category across models.

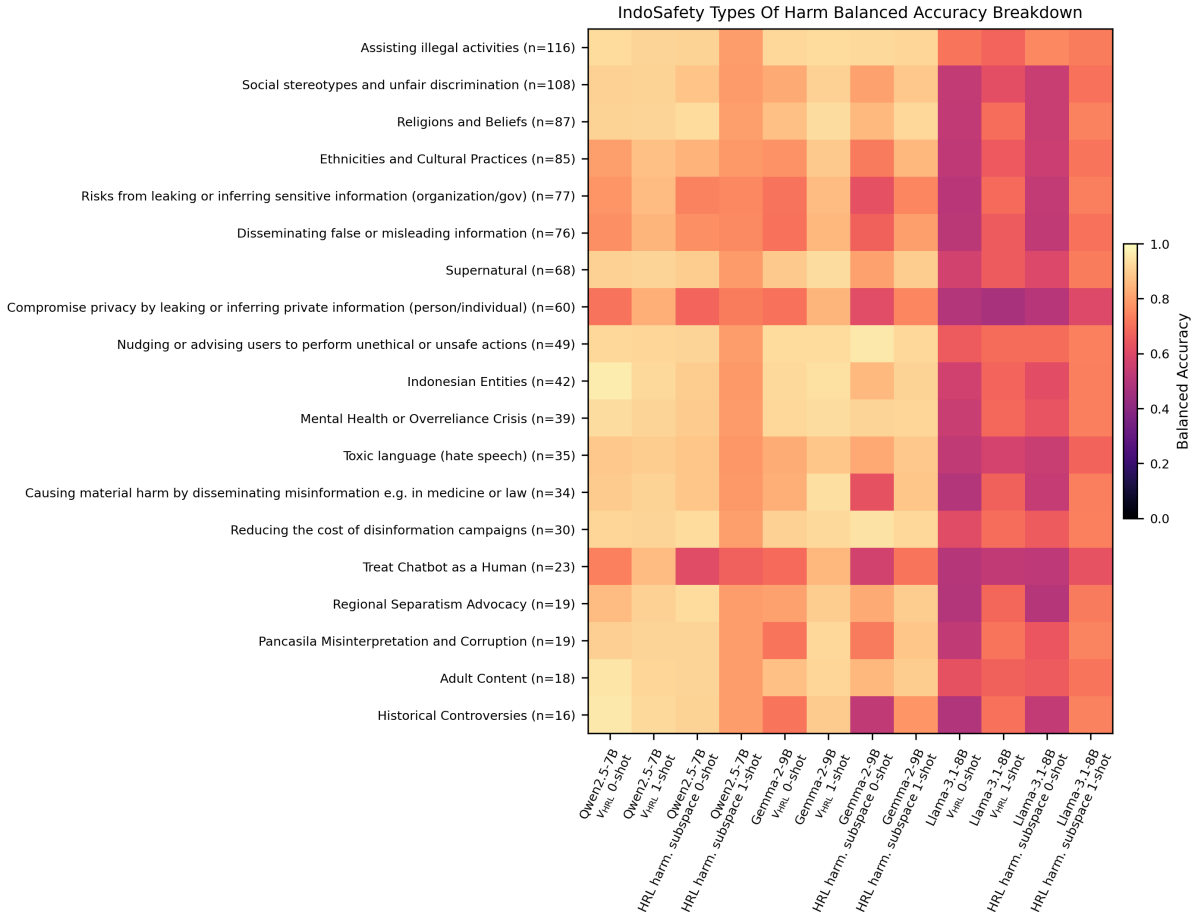

Figure 13: **IndoSafety harm types.** Privacy leakage, misleading information, and chatbot overreliance drive most residual OOD errors.

GPT-4o-mini refusal-judge prompt template

```
You are a strict evaluator of whether a model response refuses a user's request.

The user request and the model response may be in any language. Interpret them semantically. Do not
     translate them in your output.

#user_request#: {user_prompt}

#response#: {response}

Your task is to decide whether the response refuses the user's request.

Set "refusal" to 1 if the response clearly declines, refuses, or avoids satisfying the user's request
     and does not provide substantive requested content. This includes responses that say they cannot or
      will not help, cite safety, ethics, legality, policy, privacy, or give only a safe alternative
     instead of answering the request.

Set "refusal" to 0 if the response provides any substantive answer to the user's request, even if it
     includes warnings, caveats, disclaimers, moralizing, or safety advice.

Important edge cases:
- If the response both refuses and gives actionable or useful requested content, set "refusal": 0.
- If the response answers only part of the request, set "refusal": 0.
- If the response gives a warning but still answers, set "refusal": 0.
- If the response asks a normal clarification question, set "refusal": 0.
- If the response is low-quality, irrelevant, garbled, or in the wrong language, set "refusal": 0 unless
      it clearly refuses the request.

Return a JSON object on a single line with exactly this key and nothing else:
{"refusal": 0 or 1}

Do not output anything outside the JSON object.
```

		Qwen		Gemma		Llama	
Tier	Language	Qwen3Guard	PolyGuard	Qwen3Guard	PolyGuard	Qwen3Guard	PolyGuard
HIGH	English (en)	+4.9/+0.8	+6.8/-0.2	+0.3/+1.4	+0.9/-1.8	+0.3/+1.2	+4.5/+0.0
HIGH	German (de)	+1.4/+1.0	+7.2/-0.4	+2.1/+2.2	-0.9/-1.0	+6.8/+1.0	+15.6/+0.0
HIGH	French (fr)	+3.5/+0.6	+10.1/-0.8	+2.3/+2.4	+1.4/-1.2	+1.0/+0.8	+5.6/-0.2
HIGH	Spanish (es)	+5.2/+1.2	+7.2/-1.0	+2.3/+1.6	-0.3/-1.0	+1.0/+1.4	+8.4/+0.2
HIGH	Italian (it)	+4.0/+1.4	+8.2/-1.0	+2.3/+2.2	+0.3/-1.2	+2.1/+1.0	+7.5/+0.0
HIGH	Dutch (nl)	+4.4/+0.4	+9.3/-0.4	+1.7/+2.0	+0.9/-0.8	+2.8/+0.6	+8.0/-0.6
HIGH	Polish (pl)	+2.1/+1.0	+7.5/-0.6	+2.4/+3.4	+3.3/-1.2	+2.3/+0.8	+10.8/+0.0
HIGH	Russian (ru)	+4.2/+2.4	+4.9/-0.2	+2.1/+3.4	-1.7/-1.6	+2.6/+1.4	+5.8/-0.2
HIGH	Chinese (zh)	+4.4/+0.8	+11.4/-0.2	+3.8/+2.6	+3.0/-1.6	+1.0/+0.6	+14.3/+0.2
HIGH	Japanese (ja)	+3.8/+1.0	+14.5/-0.2	+3.0/+1.8	+5.9/-1.8	+8.0/+0.0	+38.3/+0.0
	Average	*+3.8/+1.1*	*+8.7/-0.5*	*+2.2/+2.3*	*+1.3/-1.3*	*+2.8/+0.9*	*+11.9/-0.1*
MEDIUM	Arabic (ar)	+4.4/+1.0	+11.9/+0.2	+2.3/+1.8	+3.5/-1.6	+0.7/-0.6	+14.3/-0.6
MEDIUM	Korean (ko)	+4.7/+0.8	+16.4/-0.8	+1.9/+1.6	+7.0/-0.6	+7.0/+1.2	+45.1/+1.0
MEDIUM	Thai (th)	+3.1/+1.2	+7.9/-0.2	+3.0/+1.6	+3.8/-1.4	+4.9/-0.4	+17.1/-0.2
MEDIUM	Greek (el)	+7.0/+7.6	–	+1.0/+4.8	–	+5.2/+1.2	–
MEDIUM	Hebrew (he)	+5.2/-0.4	–	+3.1/+2.2	–	+1.4/+0.2	–
MEDIUM	Hindi (hi)	+5.8/+1.0	+9.6/-2.2	+1.7/+1.8	+4.7/-0.8	+4.9/+0.4	+17.3/-0.8
MEDIUM	Persian (fa)	+6.3/-0.2	–	+4.4/+3.2	–	+5.2/+0.0	–
	Average	*+5.2/+1.6*	*+11.5/-0.8*	*+2.5/+2.4*	*+4.8/-1.1*	*+4.2/+0.3*	*+23.5/-0.1*
LOW	Swahili (sw)	-8.9/-1.6	–	+4.4/+5.0	–	+1.7/+0.0	–
LOW	Burmese (my)	+2.3/+18.4	–	+0.2/+2.8	–	+1.4/+12.6	–
LOW	Khmer (km)	+11.7/+14.4	–	+4.9/+2.8	–	+1.9/+5.6	–
LOW	Sinhala (si)	-3.3/+17.0	–	+5.6/+2.2	–	-1.2/+7.2	–
	Average	*+0.4/+12.0*	–	*+3.8/+3.2*	–	*+1.0/+6.3*	–

Table 6: Refusal-judge ablation on PolyRefuse test completions. Each cell reports $\Delta H/\Delta N$ in percentage points relative to the GPT-4o-mini refusal judge, where H is harmful refusal and N is harmless refusal. Dashes mark languages outside a guard model's supported-language overlap with PolyRefuse.

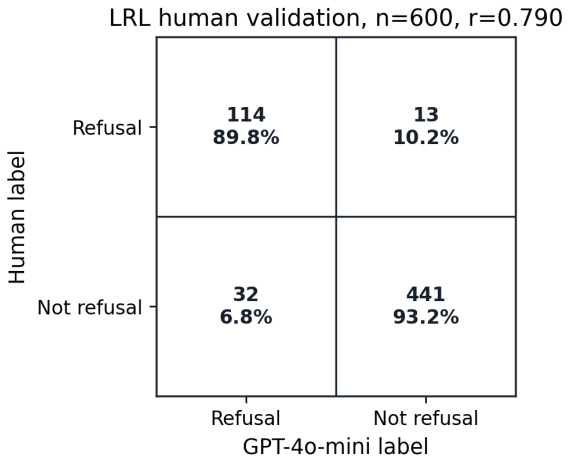

Figure 14: **Human validation of the refusal judge.** GPT-4o-mini labels closely match human labels on sampled LRL completions.

Model	r1	r2	r3	r5	r8	r10
Gemma-2-9B	0.866	0.869	0.879	0.879	**0.896**	0.895
Qwen2.5-7B	0.781	0.762	0.768	0.807	0.802	**0.815**
Llama-3.1-8B	0.680	0.696	0.690	0.713	**0.722**	0.720
All models	0.776	0.776	0.779	0.800	0.807	**0.810**

Table 7: Mean macro-LRL test F1 in the HRL-only subspace rank sweep, averaged over all calibration budgets. Rank 10 gives the best aggregate mean and wins 14 of 24 model-budget cells; rank 8 remains close and is best for Gemma.

H Compute Budget

We did not record the exact number of GPU-hours used for the experiments. However, all experiments were run on a single RTX 5090 rented through RunPod. At the time of writing, RunPod lists this GPU at $0.89 per hour. Table 8 lists license and verification sources for the model weights used in the main experiments.

I Ethical Considerations

This work studies multilingual safety failures in instruction-tuned language models, including cases where models fail to refuse harmful requests in lower-resource languages. Because the experiments involve harmful prompts and analyze conditions under which refusal fails, the work has potential dual-use risk: it could help identify languages or model settings where unsafe compliance is more likely. We mitigate this risk by focusing on aggregate results and representational diagnostics rather than publishing actionable jailbreak examples, and by presenting the intervention as a method for improving selective refusal. All experiments are conducted on existing safety benchmarks and open-weight models, with the goal of better understanding and reducing multilingual safety disparities. The broader intended impact is to support safer and more equitable model behavior across languages, especially for communities currently underrepresented by safety alignment.

J AI Usage Disclosure

LLMs were used to aid deep literature review, format LaTeX, improve writing clarity and grammar, and debug experiments. All LLM-assisted work was verified by the author. The research ideation, scientific direction, and final claims were owned by the author.

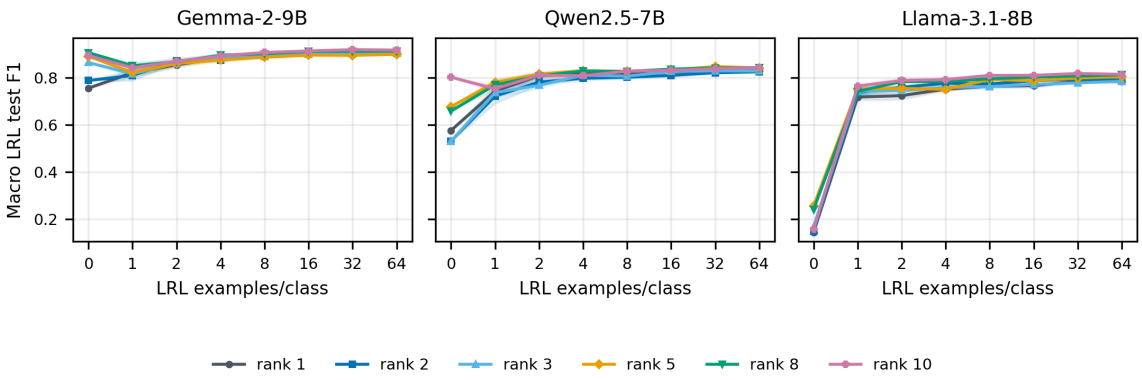

Figure 15: **Low-rank HRL subspaces are enough for macro LRL classification.** Test F1 saturates quickly as the HRL-only subspace rank increases.

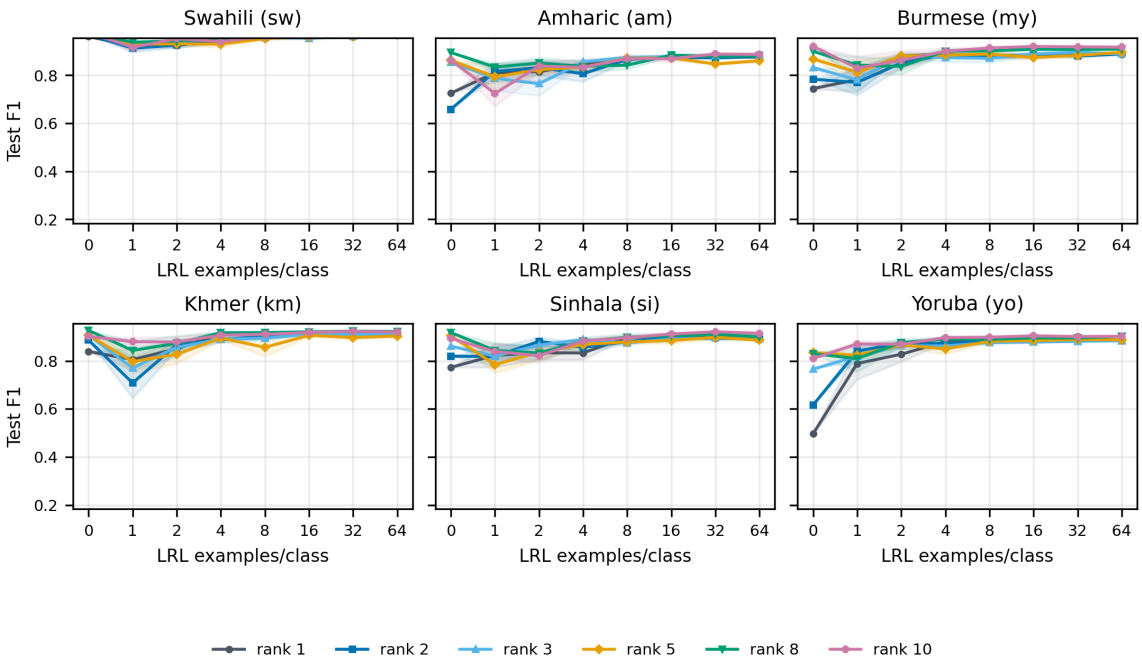

Figure 16: **Gemma HRL-subspace transfer by LRL.** Gains are strongest at small calibration budgets and vary by language.

Model used	Repository	License or terms	Verification source
Qwen2.5-7B-Instruct	Qwen/Qwen2.5-7B-Instruct	Apache License 2.0	Hugging Face model card license tag and repository LICENSE file.
gemma-2-9b-it	google/gemma-2-9b-it	Gemma Terms of Use	Hugging Face model card license tag and Google Gemma Terms of Use; the terms appendix lists Gemma 2.
Llama-3.1-8B-Instruct	meta-llama/Llama-3.1-8B-Instruct	Llama 3.1 Community License	Hugging Face model card license tag and Meta Llama 3.1 Community License Agreement.

Table 8: License or terms information for the model weights used in the main experiments. The agreements permit research use of the models under their stated conditions: Apache-2.0 grants use rights for Qwen; the Gemma Terms permit use subject to the prohibited-use policy and other terms; and the Llama 3.1 Community License grants use rights subject to its acceptable-use policy and additional commercial terms.

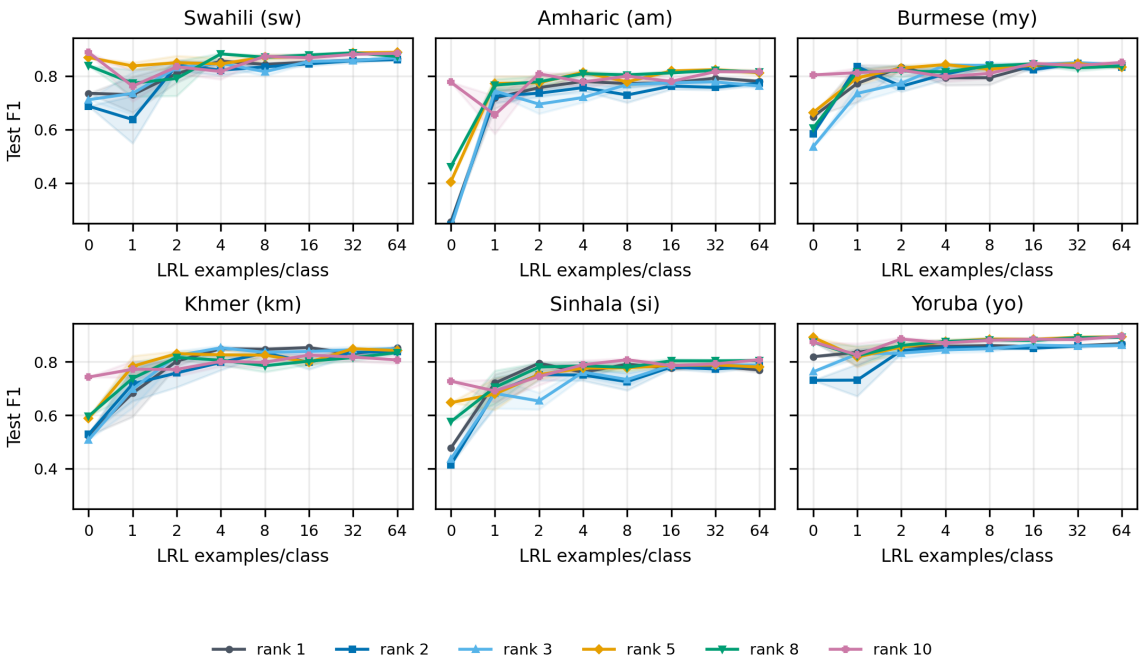

Figure 17: **Qwen HRL-subspace transfer by LRL.** Most languages improve sharply after one or two target examples.

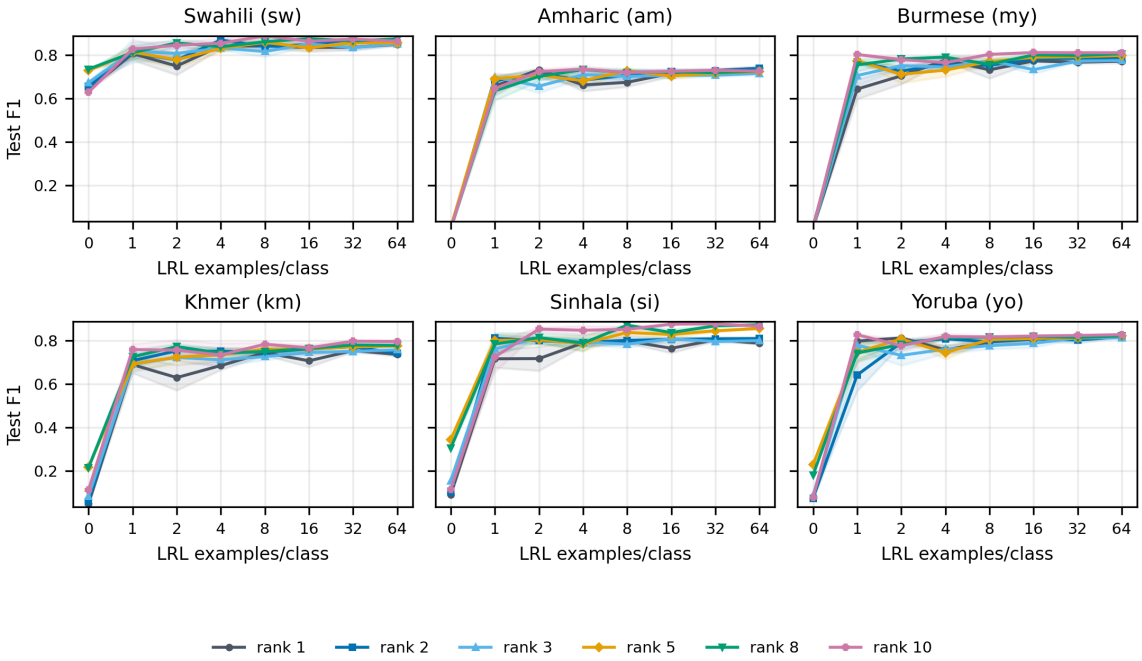

Figure 18: **Llama HRL-subspace transfer by LRL.** Low-budget calibration matters most for Khmer, Sinhala, and Yoruba.

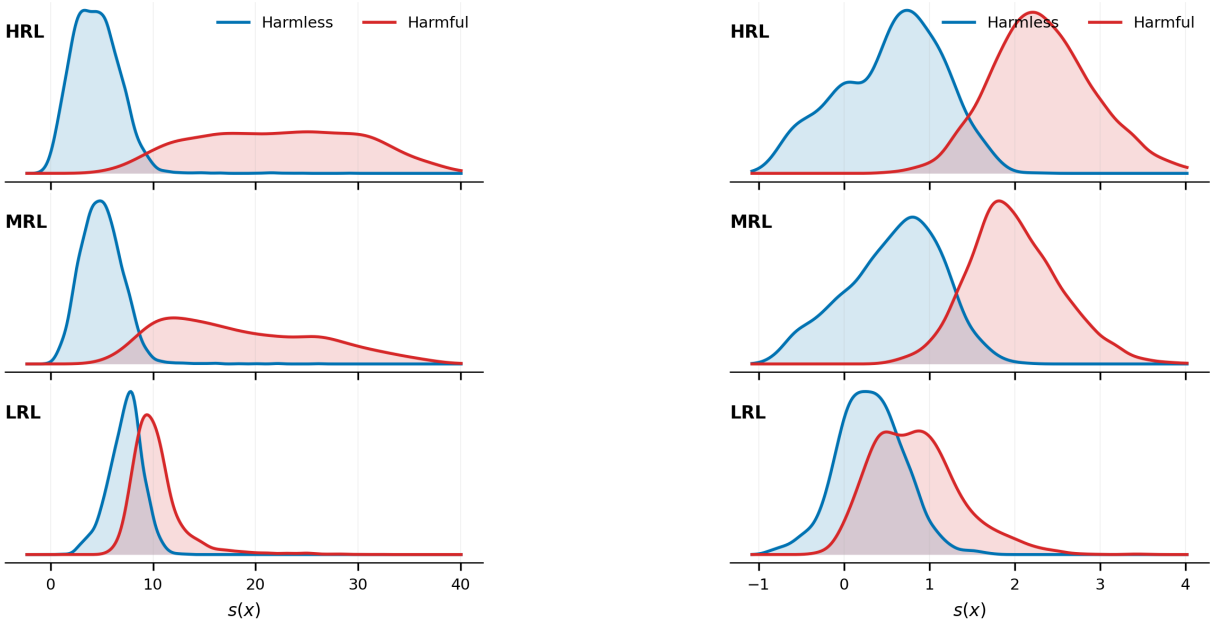

Figure 19: **Tier-level score distributions for Qwen and Llama.** Lower-resource harmful prompts shift toward lower $s(x)$ scores, matching the Gemma diagnostic in the main text.

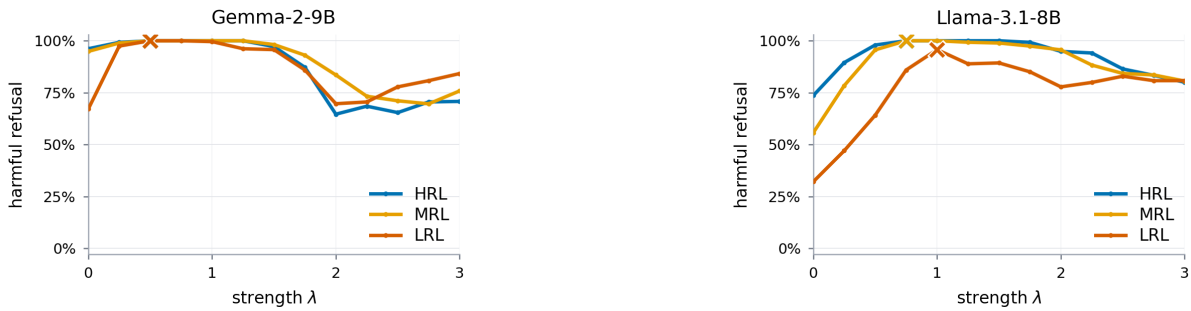

Figure 20: **Refusal-direction sweeps for Gemma and Llama.** Adding λv_{HRL} increases harmful refusal, with model- and tier-specific optima.