Beyond the Final Layer: Intermediate Representations for Better Multilingual Calibration in Large Language Models

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Abstract

Confidence calibration, the alignment of a model's predicted confidence with its actual accuracy, is crucial for the reliable deployment of Large Language Models (LLMs). However, this critical property remains largely under-explored in multilingual contexts. In this work, we conduct the first large-scale, systematic studies of multilingual calibration across six model families and over 100 languages, revealing that non-English languages suffer from systematically worse calibration. To diagnose this, we investigate the model's internal representations and find that the final layer, biased by English-centric training, provides a poor signal for multilingual confidence. In contrast, our layer-wise analysis uncovers a key insight that late-intermediate layers consistently offer a more reliable and better-calibrated signal. Building on this, we introduce a suite of training-free methods, including Language-Aware Confidence Ensemble (LACE), which adaptively selects an optimal ensemble of layers for each specific language. Our study highlights the hidden costs of English-centric alignment and offer a new path toward building more globally equitable and trustworthy LLMs by looking beyond the final layer.

1 Introduction

Calibration in machine learning denotes the alignment between a model's predicted confidence and the empirical probability that its predictions are correct [Guo et al., 2017, Geng et al., 2024, Zhang et al., 2025a,b].[2] A model is perfectly calibrated if predictions assigned 80% confidence are correct approximately 80% of the time. Calibration is particularly critical for large language models (LLMs) in high-stakes applications such as medical diagnosis, legal advice, and decision support, where miscalibration can amplify harm [Zhang et al., 2024b, Yang et al., 2024b, 2025]. Well-calibrated LLMs make their reliability explicit and interpretable, improving downstream trust and safety.

Despite its importance, most calibration work in LLMs focused on English [Xue et al., 2024]. This reflects what Ruder et al. [2022] termed *Square One Bias*: progress in research often advances along a single axis (e.g., English alignment or multilingual coverage), while the intersection—multilingual calibration—remains underexplored. Existing studies examine few languages, rely on machine-translated data, and consider a narrow set of models [Xue et al., 2024, Yang et al., 2023].

To address this gap, we conduct the first large-scale systematic studies of multilingual calibration. Our analysis spans six major model families and over 100 languages, using high-quality, human-curated

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[2] In this paper, we distinguish between calibration as a *property* and as a *process*. We use the term *calibration* to refer to the property of a model's confidence being well-aligned with its accuracy. In contrast, the methods used to achieve this alignment are referred to as *calibration methods* or a *calibrator*.

benchmarks (MMMLU and Belebele) with $\sim 10^5$ instances. Our findings reveal a stark disparity. Non-English languages consistently exhibit not only lower accuracy but also dramatically worse calibration—for instance, LLaMA-3's Expected Calibration Error (ECE) is nearly five times higher on average for non-English than for English (23.1% vs. 4.6%). Prior work often treats miscalibration in LLMs primarily as overconfidence [Zhang et al., 2024d, Chhikara, 2025]. We instead reveal **distinct miscalibration patterns** tied to training priorities. English-aligned models like LLaMA3 struggle to maintain calibration quality beyond English, whereas multilingual-first models like Aya are systematically over-confident across the board. This suggests that current alignment strategies fail to generalize, creating unreliable models for non-English languages.

Seeking to understand the architectural source of this miscalibration, we challenge the conventional practice of extracting confidence scores solely from the model's final layer. Inspired by work showing intermediate layers encode more language-agnostic representations [Bandarkar et al., 2024b, Wendler et al., 2024], we hypothesize that the final layer, heavily **biased** by English-dominated training, provides a **sub-optimal** signal for multilingual confidence. A comprehensive layer-wise analysis reveals an interesting dichotomy: while English calibration improves *monotonically* with model depth, peaking at the final layer, multilingual calibration follows *a different trajectory*. For nearly all non-English languages, we find that *late-intermediate layers* consistently provide better-calibrated confidence estimates. This discovery of a latent, more reliable calibration signal hidden deeper within the model's architecture is a key finding of our work.

This core insight motivates our primary methodological contribution: a set of simple yet effective training-free calibration methods that leverage these intermediate representations. We compare three confidence elicitation strategies: the *best layer* method identifies and selects the single most calibrated intermediate layer, the *good layers-ensemble* approach aggregates signals from multiple layers to improve robustness, and finally we propose *LACE* (Language-aware Confidence Ensemble), a novel method that adaptively tailors layer selection to each target language. Our methods yield substantial and consistent improvements in multilingual calibration across all models. Crucially, they are orthogonal and complementary to traditional post-hoc techniques; combining *LACE* with calibration methods like Temperature Scaling [Guo et al., 2017] leads to further improvements.

Our contributions are threefold: (1) We provide a comprehensive empirical analysis of multilingual LLM calibration, revealing systematic and significant disparities between English and over 100 other languages. (2) We are the first to conduct a layer-wise investigation of multilingual calibration, discovering that intermediate layers offer a more reliable calibration signal than the final, English-biased layer. (3) We introduce novel, training-free calibration methods that leverage intermediate representations, demonstrating their effectiveness in closing the cross-lingual calibration gap.

2 Related Work

Multilingual Calibration Recent work has highlighted that modern LLMs, despite their strong performance, frequently struggle with calibration in their predictions [Xiong et al., 2024, Zhang et al., 2024c]. Parallel studies document language-specific biases in LLMs [Zhang et al., 2024a, Qin et al., 2025]. Yet calibration in multilingual settings remains underexplored. Ahuja et al. [2022] first established that multilingual models like mBERT and XLM-R are poorly calibrated, especially for low-resource languages like Swahili. Xue et al. [2024] conducted a confidence estimation study across various models, covering both language-agnostic and language-specific tasks, but datasets in their study included only 5 languages and were machine-translated which can potentially import bias [Vanmassenhove et al., 2021, Choenni et al., 2024]. Our work distinguishes itself by presenting the first systematic evaluation of multilingual calibration across high-quality, human-curated datasets spanning over 100 languages and covering six prominent LLM families. Additionally, all prior studies have primarily documented calibration issues at the final output layer, none have examined confidence behaviour in depth or investigated its architectural origins, leaving the gap for our research.

Layer-wise Representations A growing body of research investigates the functional specialization of layers within multilingual transformers. It is widely observed that intermediate layers encode cross-lingual semantic knowledge in a largely language-agnostic manner, forming a shared representational space [Bandarkar et al., 2024b]. In contrast, the final layers tend to be more language-specific, adapting these general representations to handle surface-level features like syntax and word order for the target language. Recent studies on predominantly English-trained LLMs, such as LLaMA,

Language	LLaMA3				Aya			
	ECE↓	BRIER↓	AUROC↑	Accuracy	ECE↓	BRIER↓	AUROC↑	Accuracy
Arabic	33.06	24.37	61.00	38.20	28.41	33.79	71.49	45.20
Bengali	24.93	23.39	58.44	35.20	29.01	31.48	60.01	31.30
German	25.81	24.92	65.36	44.40	26.54	33.51	69.70	53.00
Spanish	18.21	21.89	71.65	52.00	28.17	31.86	71.12	51.10
French	13.87	22.75	71.39	51.30	23.80	32.72	70.69	53.40
Hindi	28.31	24.28	62.07	39.90	30.21	34.98	70.08	42.30
Indonesian	19.67	23.76	66.25	45.00	27.88	31.54	70.85	51.20
Italian	21.19	22.74	71.57	51.80	26.65	30.33	71.76	52.70
Japanese	28.36	27.27	61.73	43.00	16.30	26.26	69.92	46.70
Korean	30.86	25.06	62.59	42.50	32.07	37.09	72.06	45.00
Portuguese	10.51	21.76	71.37	50.40	27.33	31.42	70.71	53.50
Swahili	23.84	21.45	61.10	32.20	32.01	36.72	58.23	31.30
Yoruba	8.18	19.43	58.00	27.40	30.11	28.56	60.73	26.40
Chinese	41.94	19.56	50.63	23.10	17.12	28.75	67.35	52.20
English	**4.61**	**17.63**	**80.36**	**61.20**	**20.66**	**25.30**	**74.65**	**57.40**
Avg. Non-English	23.12	22.95	64.06	41.47	26.77	31.97	68.26	45.49
Avg. Low-Resource	23.00	22.78	61.14	36.32	29.60	32.84	65.23	37.95
Avg. High-Resource	21.71	22.62	67.41	46.63	24.29	30.80	70.88	51.67
Avg. Non-Latin-Script	27.44	23.10	59.44	35.19	26.90	32.20	66.23	40.05
Avg. Latin-Script	16.27	22.21	71.14	50.87	25.86	30.95	71.35	53.19
Average (All)	22.22	22.68	64.90	42.51	26.42	31.62	68.62	46.18

Table 1: Multilingual performance of **LLaMA3** (left) and **Aya** (right) on the MMMLU dataset. Metrics include ECE, Brier Score, AUROC, and Accuracy. All numbers are in percentages.

suggest a more specific mechanism: the middle layers tend to operate in a largely language-agnostic space, where multilingual inputs are mapped into shared internal representations that often resemble English-like structures [Wendler et al., 2024, Kojima et al., 2024, Alabi et al., 2024]. This hypothesis highlights that while surface forms differ across languages, the model internally normalizes them into a common representational layer before decoding back into the target language in the final layers, which explains the empirical success of prompting strategies that explicitly ask the model to "think in English" before generating a response in another language, as this aligns with the model's internal processing pathway [Shi et al., 2023, Zhang et al., 2024e]. Our work builds on these insights by investigating how this layer-wise specialization—particularly the language-neutral properties of intermediate representations—affects calibration across languages.

3 Benchmarking Multilingual Calibration

In this section, we systematically examine the multilingual calibration in leading LLMs. We first detail our experimental setup using human-curated datasets, and then present our analysis of the models' performance across a diverse set of over 100 languages.

3.1 Experimental Setup

Datasets and Models We focus on multilingual Multiple-Choice Question-Answering (MCQA) datasets because it provides us with controllable ways of confidence measurement: (1) **MMMLU** [Hendrycks et al., 2021] (15 languages), (2) **Belebele** [Bandarkar et al., 2024a] (122 languages). Compared to previous works, the datasets we use consist of high-quality human-translated items, covering a much larger range of languages and much more data points (at the scale of $\sim 10^5$ instances). All experiments are conducted using an eight-shot prompting setup in its respective language. We evaluate a range of recent LLMs, including **LLaMA3**, **Qwen2.5**, **Mistral**, **Aya**, **DeepSeek**, and **Phi** (see Appendix B.1 for details). Regarding the confidence elicitation method, we adopt the standard approach in MCQA, using the output probability of the selected answer choice: $\text{Conf}(x) = \max_{i \in 1,\dots,K} p_i$, where $\sum_{i=1}^{K} p_i = 1$.

Metrics We evaluate calibration using expected calibration error (ECE; Guo et al., 2017) and the Brier score [Brier, 1950]. To measure model's ability to discriminate between correct and incorrect predictions, we also report AUROC [Fawcett, 2006]. Lower ECE and Brier scores indicate better calibration; higher AUROC indicates stronger discrimination ability.

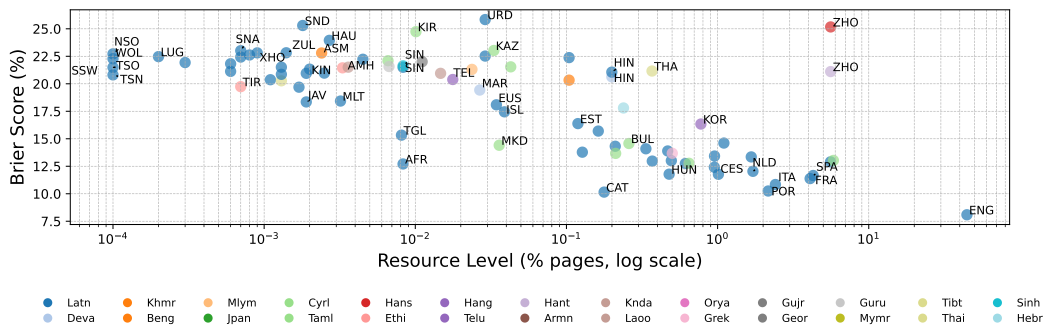


Figure 1: Relationship between resource level and Brier score for the LLaMA3 model on the Belebele benchmark. Each point represents a language, and same colour indicates same writing system. Correlations: Spearman $\rho = -0.59$, $p < 10^{-8}$; Kendall $\tau = -0.43$, $p < 10^{-8}$; Pearson $r = -0.39$, $p < 0.001$; indicating that higher-resourced languages tend to achieve better calibration.

3.2 Results

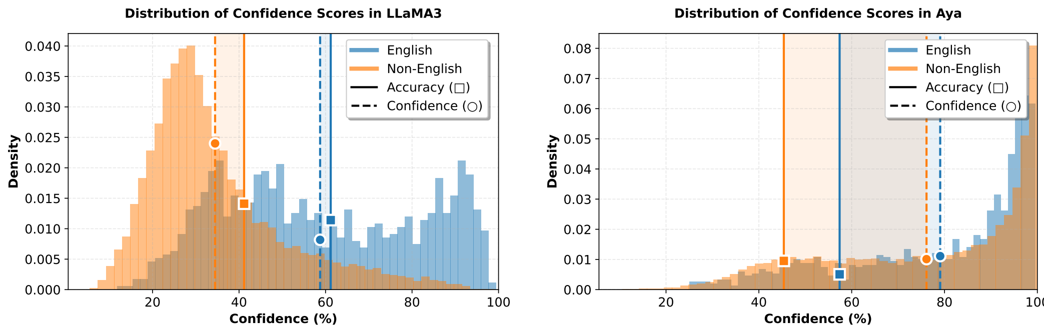
Our results of models (LLaMA3 and Aya), shown in Table 1 for MMMLU and visualized in Figure 1 for Belebele (see Appendix B.3 for group definitions). Additional MMMLU results are provided in the Appendix, including Mistral (Table 3), Qwen2.5 (Table 4), Phi (Table 5), and Deepseek (Table 6). Comprehensive Belebele results for all models appear in Table 8, 9, 10, 11, 12, and 13 (see Appendix B.5). Our key findings are as follows:

Not only are LMs more accurate but also more calibrated in English. As shown in Table 1, non-English languages consistently underperform English in both accuracy and calibration. The average ECE for non-English LLaMA3 is 23.12%, far higher than the 4.61% for English, and Aya shows a similar pattern (26.77% v.s. 20.66%), highlighting that the language imbalance persists despite claims of improved multilingual capabilities [Dang et al., 2024]. This discrepancy is evident in Brier Score and also AUROC. We also observe that Non-English languages show a much higher proportion of *underconfident correct predictions*—where model predicts correctly but has less than 50% confidence—at 78.8% compared to only 25.7% for English (see Table 7 in Appendix B.4). Moreover, in English the model assigns on average 23.8% higher confidence to predictions that are correct than to incorrect, whereas in non-English languages this margin is only 6.3%.

Calibration correlates with language resource availability. Table 1 suggests a calibration gap between low-resourced and high-resourced languages, for example, Hindi and Swahili show a comparatively worse calibration in both models. To further illustrate this, we plot the resource level[3] and calibration for all languages in Figure 1. We find that low-resource languages generally have much higher calibration error. We observe Spearman's correlation $\rho = -0.59$ ($p < 10^{-9}$) with Brier score and $\rho = 0.66$ ($p < 10^{-12}$) with AUROC, indicating that data-rich languages are better calibrated and show stronger discrimination ability. This pattern suggests that calibration is influenced by the representation of a language in the pre-training corpus.

***Square One Bias*: Differences in confidence distribution reflect training/alignment priorities.** Plotting the confidence distributions of the tested models reveals distinct calibration patterns that reflect their training priorities. For LLaMA-3 (Figure 2a), the English setting shows good calibration (ECE = 4.61), whereas the non-English setting exhibits a different confidence curve and greater under-confidence. By contrast, Aya's confidence distributions in English vs.non-English are similar in shape (Figure2b) but are strongly miscalibrated in both, showing a significant right skew (overconfidence). We argue that these patterns reflect the models' training and alignment policies. LLaMA-3 is documented for alignment efforts through supervised fine-tuning, preference ranking, and safety pipelines [Grattafiori et al., 2024], but this work appears primarily English-focused, leaving calibration in

[3] Since LLaMA3 does not release the exact training data, we use the Common Crawl dataset (`CC-MAIN-2025-30`; Common Crawl Foundation, 2025)'s percentage of web pages available per language from the crawl as a proxy for global resource availability across languages.



(a) LLaMA3 confidence distribution

(b) Aya confidence distribution

Figure 2: Confidence distributions for English v.s. Non-English samples in (a) LLaMA3 and (b) Aya models. The histograms show the density of model confidence scores. The overall distributions differ substantially between English and Non-English inputs in LLaMA3, and the gap between confidence (dashed lines) and accuracy (solid lines) is much larger for Aya.

other languages largely unaddressed. Aya, by contrast, prioritizes multilingual coverage [Üstün et al., 2024, Dang et al., 2024] but pays less attention to calibration or caution in predictions. Together, these results echo the *Square One Bias* [Ruder et al., 2022]: LLaMA-3 advances mainly in English alignment and safety, while Aya advances in multilingual ability, each neglecting the complementary dimension required for robust multilingual calibration. Confidence behaviour of other models can be found in Figure 6 in Appendix B.4.

4 Mid-Layers Reveal Better Calibration

Inspired by recent insights in layer-wise multilingual representations [Bandarkar et al., 2024b, Wendler et al., 2024], we examine how confidence evolves throughout the model's depth to understand the source of the poor calibration observed in §3. Our analysis reveals that the final layers, which are over-specialized in English, can **harm the calibration for other languages**.

4.1 Methodology for Early-Decoded Confidence Estimation

We investigate the following question: *Is it possible to identify intermediate representations that elicit better calibrated confidence scores with respect to final-layer accuracy?* We adopt a layer-wise probing technique inspired by the early exiting paradigm [Elbayad et al., 2020] to offer a new way of confidence estimation. Instead of applying the modelling head only to the final hidden state, we attach it to each intermediate transformer layer. This allows us to extract logits and compute prediction confidence from every layer, providing a granular view of the model's decision-making process.

Formally, let $\mathbf{h}_\ell \in \mathbb{R}^d$ denote the hidden representation at layer ℓ, where $\ell = 1, \ldots, L$, and d is the dimensionality of the hidden state. We apply the original language modeling head, with weight matrix $W \in \mathbb{R}^{V \times d}$, to compute the logits at each layer:

$$\mathbf{z}_\ell = W\mathbf{h}_\ell$$

where $\mathbf{z}_\ell \in \mathbb{R}^V$ are the unnormalized token logits over the vocabulary of size V. These logits are then converted into probabilities using the softmax function:

$$\mathbf{p}_\ell = \mathrm{softmax}(\mathbf{z}_\ell), \quad \sum_{v=1}^{V} [\mathbf{p}_\ell]_v = 1,$$

With the $\mathbf{p}_\ell$, we *trace* the token ultimately predicted at the final layer, $\hat{y}_L = \arg\max_v [\mathbf{p}_L]_v$, back through the intermediate layers. At each layer ℓ, we then define the confidence score as the probability mass that this layer assigns to the final prediction, calibration is then evaluated by comparing these $\mathrm{Conf}_\ell(x)$ with the prediction accuracy determined at the final layer $\hat{y}_L$:

$$\mathrm{Conf}_\ell(x) = [\mathbf{p}_\ell]_{\hat{y}_L}, \quad \mathrm{ECE}_\ell = \mathrm{ECE}\Big(\{(\mathrm{Conf}_\ell(x),\ \mathbf{1}\{\hat{y}_L = y\})\}\Big).$$

where $\mathbf{1}\{\hat{y}_L = y\}$ is the indicator function of whether the final-layer prediction is correct.

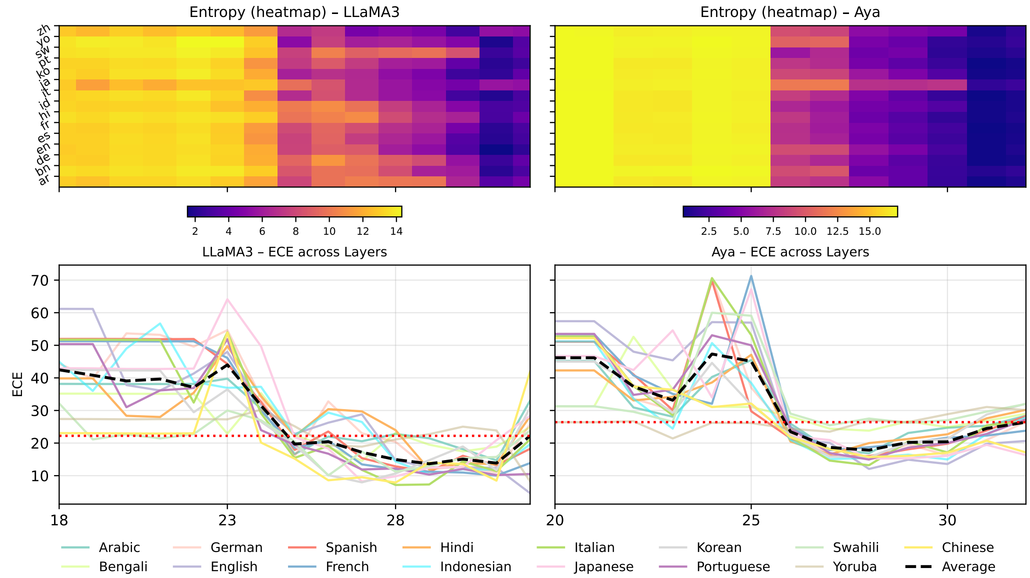


Figure 3: ECE v.s. entropy across layers on the MMMLU subset for LLaMA3 and Aya. In the multilingual setting, many languages achieve their **best** ECE in **intermediate layers** (e.g., 25-32 for LLaMA3 and 26-32 for Aya), after which calibration quality degrades towards the final layer. This contrasts with the English-only setting, where calibration improves monotonically (see Figure 7). Notably, the *sweet spot* in calibration coincides with the sharp drop in entropy.

4.2 Multilingual Language Models Calibrate Earlier

Last layer shows best calibration level in the English-only setting. As shown in Figure 7 (see Appendix C.1) for LLaMA3, our layer-wise analysis shows a clear trend: the layer-predicted confidence calibration improves monotonically with layer depth. This aligns with the conventional understanding [Tenney et al., 2019] that representations become progressively more refined and task-specific, leading to better calibration as data propagates through the network.

Multilingual settings reveal best calibration in late intermediate layers. However, our analysis reveals a different pattern in the multilingual context. As illustrated in Figure 3, the best calibration performance for many languages **does not** occur at the final layer. Instead, we find a *sweet spot* with lower ECE in the late-intermediate layers (between layers 24-end for LLaMA3 and 26-end for Aya, both are 32-layer models), after which calibration quality *worsens* to the final output layer. Concretely, for LLaMA3, selecting layer 29 results in an average ΔECE of 8.57, while for Aya layer 28 results a comparable 8.59. Notably, this turning point in calibration quality aligns with the trend in entropy: as entropy begins to drop sharply in these intermediate layers, ECE also decreases.

Per-language calibration trends reveal that late-intermediate layer improves calibration for most non-English languages, with a slight trade-off for English. To further explore these dynamics, Figure 14 presents per-language reliability diagrams for nine languages, comparing the selected intermediate layer (Layer 29) against the final layer of LLaMA3. Nearly all non-English languages benefit greatly from moving away from the final layer: their reliability curves align more closely with the diagonal, and ECE decreases substantially. For example, German and Hindi show reductions in ECE of more than 13% and 16%, respectively. In contrast, calibration for English appears to degrade slightly at intermediate layers. Since the final layer already exhibits strong calibration for English, earlier layers offer no additional benefit. This highlights a potential bias introduced during pretraining, where the model overfits to English patterns or introduces noise during the final stages of adaptation. While the degree of improvement varies across languages, the trend remains consistent across diverse linguistic families and scripts. This suggests that the effect is not language-specific but rather a systematic property of multilingual calibration. Additional examples are provided in Appendix C.3.

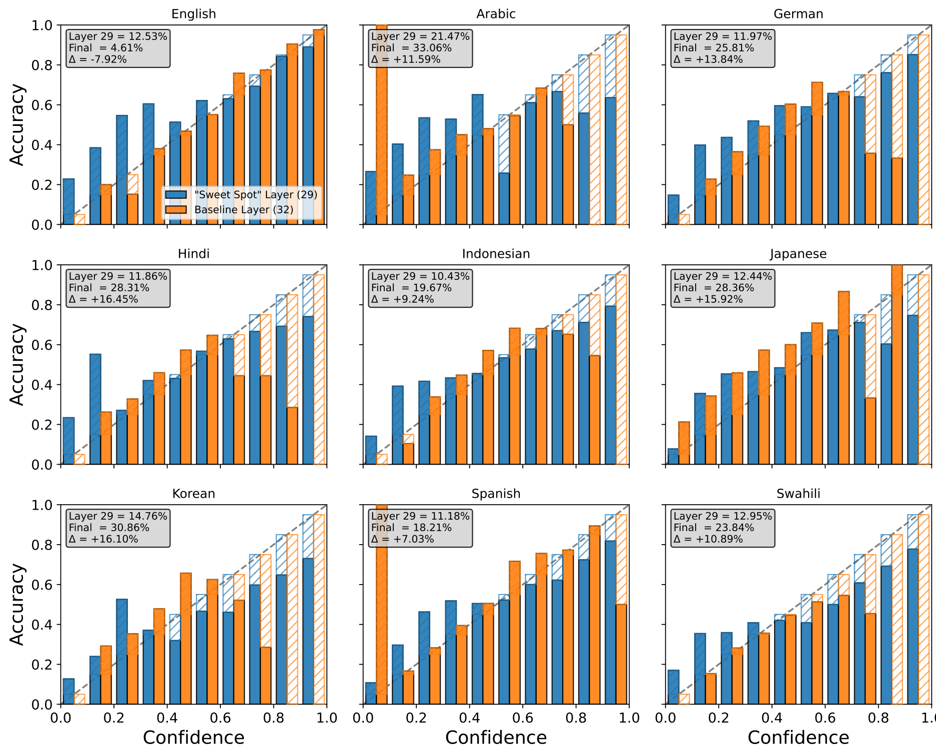


Figure 4: **Per-language calibration reliability diagrams for LLaMA3.** Each panel shows a reliability histogram with evenly spaced confidence bins. **Blue** bars correspond to the chosen intermediate layer (Layer 29), and **orange** bars correspond to the original final layer. The dashed diagonal is the perfectly calibrated line ($y = x$). Hatched overlays indicate the absolute calibration gap within each bin. The inset reports ECE (%) for both layers and the change $\Delta\text{ECE} = \text{ECE}_{\text{Final}} - \text{ECE}_{29}$ (positive values denote improved calibration at Layer 29).

The mid-layer calibration peak is a robust finding across models. Our observation is not isolated to a single model or metric. We consistently find this pattern across multiple architectures and evaluation metrics, as detailed in the Appendix C.2. In LLaMA3 (Figure 8), Aya (Figure 9), Mistral (Figure 10), and others, multilingual models exhibit a latent calibration optimum not at the decoding layer but in late-intermediate layers. This finding challenges the common practice to use final-layer probabilities to calculate model confidence, and it opens avenues for layer-aware calibration strategies that explicitly exploit these "sweet spots" to mitigate cross-lingual disparities, which motivates the novel calibration methods proposed in the next section.

5 Improving Multilingual Calibration

5.1 Multilingual Calibration Methods

Our observations in Section 4 motivate confidence estimators that exploit intermediate representations. We explore to extract confidence in three different ways:

- **Final layer (baseline).** We follow the standard practice in prior work by using the model's final layer to derive probabilities, which serves as our baseline.
- **Best layer.** We identify the *best layer* as the one that achieves the lowest average calibration error across languages. From this layer, we extract probability estimates following the procedure in Section 4.1. The best layer ℓ^* is selected using a separate validation set and defined as:

$$\ell^* = \arg\min_{\ell \in \{1,\ldots,L\}} \text{ECE}_\ell^{\text{avg}}.$$

- **Good layers ensemble.** We consider the set of layers (*good layers*) whose multilingual calibration outperforms the final layer. To obtain confidence estimates, we average the predictive distributions across these layers $\mathcal{G}$, this reduces layer-specific noise while pooling calibration-aware signals:

$$\mathcal{G} \;=\; \{\ell : \mathrm{ECE}_\ell^{\mathrm{avg}} < \mathrm{ECE}_L^{\mathrm{avg}}\}, \qquad \mathbf{p}_{\mathrm{ensemble}} \;=\; \frac{1}{|\mathcal{G}|}\sum_{\ell\in\mathcal{G}} \mathbf{p}_\ell.$$

Combining with Classical Post-hoc Calibration. Since confidence elicitation and calibration are orthogonal approaches, we further test whether the proposed elicitation methods can be enhanced by standard post-hoc calibration techniques such as Temperature Scaling [Guo et al., 2017] and Isotonic Regression [Zadrozny and Elkan, 2002], which operate independently of how probabilities were obtained [Kadavath et al., 2022, Minderer et al., 2021]. We adopt a two-stage pipeline:

$$\mathbf{p}_{\mathrm{final}} \;=\; \mathrm{Calibrate}\big(\mathbf{p}_{\mathrm{intermediate}}\big)\,,$$

where $\mathbf{p}_{\mathrm{intermediate}}$ comes from the confidence scores discussed above. See Appendix D for details.

Language-Aware Confidence Ensemble. The approaches described above work in a global setting that optimizes for holistic performance across languages. However, if we aim to optimize for a specific language, we can pursue more tailored strategies to address unique calibration dynamics. To that end, we introduce a novel approach *Language-Aware Confidence Ensemble* (LACE), inspired by our layerwise analysis (Section 4) and by language-specific methods that adaptively use different layers for different languages.

For each language k, we predict confidence from layers that are better calibrated than the final layer,

$$\mathcal{G}^{(k)} \;=\; \{\ell \;:\; \mathrm{ECE}_\ell^{(k)} < \mathrm{ECE}_L^{(k)}\}, \quad \mathbf{p}_{\mathrm{ensemble}}^{(k)} \;=\; \tfrac{1}{|\mathcal{G}^{(k)}|}\sum_{\ell\in\mathcal{G}^{(k)}} \mathbf{p}_\ell^{(k)},$$

and learn a language-specific calibrator mapping:

$$\mathbf{p}_{\mathrm{final}}^{(k)} \;=\; \mathrm{Calibrate}^{(k)}\big(\mathbf{p}_{\mathrm{ensemble}}^{(k)}\big).$$

LACE is effective for three reasons. First, per-language layer selection avoids negative transfer from layers that are miscalibrated for the target language. Second, ensembling over the selected layers reduces variance while preserving language-relevant signals. Third, the method is modular and low-overhead: it reuses intermediate representations and remains compatible with standard post-hoc mappings. We report macro-averaged results across languages.

Experiment Setup We use the data from Section 4 as a held-out validation set and evaluate on a separate MMMLU test split. Both splits are balanced across languages, with a total of 30K examples. For Belebele, we construct a comparable evaluation set with 24K examples overall with a similar validation/test split.

5.2 Calibration Results

Intermediate-layer confidence shows better calibration than final-layer confidence. Figure 5 shows that moving from Best Layer to Good-Layers Ensemble to LACE yields progressive improvements in calibration. Detailed numbers are reported in Table 2 for both MMLU and Belebele. Note that occasional drops in AUROC occur because discrimination and calibration are not necessarily correlated (Gao et al., 2022, Carriero et al., 2024), and our layer selection is based on ECE rather than AUROC. Finally, by tailoring layer selection and calibration to each language, LACE achieves the best overall results, with ECE as low as 5.96 on LLaMA3.

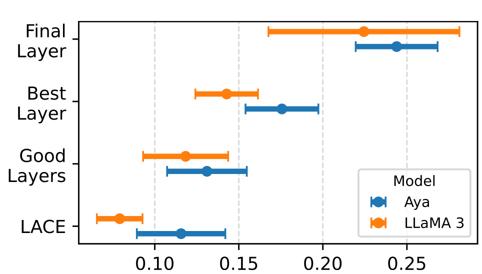


Figure 5: Forest plot of average ECE in MMMLU, with means and 95% CIs.

Method	MMMLU						Belebele					
	LLaMA3 (Acc. = 43.2%)			**Aya** (Acc. = 48.8%)			**LLaMA3** (Acc. = 68.6%)			**Aya** (Acc. = 67.8%)		
	ECE	**Brier**	**AUROC**	**ECE**	**Brier**	**AUROC**	**ECE**	**Brier**	**AUROC**	**ECE**	**Brier**	**AUROC**
FINAL LAYER BASELINE†	22.44	23.03	64.05	24.39	30.45	68.31	17.68	20.38	69.01	15.73	19.08	**72.92**
▷ *(+Temperature Scaling)*	23.35	22.59	64.05	15.40	23.76	68.31	17.63	20.39	69.01	10.66	17.19	72.92
▷ *(+Isotonic Regression)*	20.23	22.55	63.47	9.15	22.02	68.07	11.09	19.07	68.85	8.33	16.44	72.78
Intermediate Layer Calibration (Global Selection)												
BEST LAYER†	14.28	22.78	71.44	17.57	27.08	66.68	13.67	18.28	71.33	15.40	20.06	66.79
▷ *(+Temperature Scaling)*	13.71	20.60	71.44	9.34	22.52	66.68	13.12	17.52	71.34	14.99	19.16	66.79
▷ *(+Isotonic Regression)*	13.12	20.80	71.28	10.66	22.46	66.26	12.40	17.39	71.48	14.02	19.00	66.80
GOOD LAYERS ENSEMBLE†	11.84	20.23	**73.91**	13.10	23.78	**68.62**	10.78	15.59	**76.26**	11.47	18.00	70.24
▷ *(+Temperature Scaling)*	11.30	20.01	73.91	10.23	22.21	68.62	10.49	15.62	76.26	11.81	17.57	70.24
▷ *(+Isotonic Regression)*	9.60	19.90	73.49	7.71	21.82	68.25	10.16	15.54	76.07	10.42	17.48	70.31
Intermediate Layer Calibration (LACE)												
LANGUAGE-AWARE ENSEMBLE‡	5.96	20.51	72.94	11.42	22.70	68.38	7.05	**14.35**	75.61	10.22	17.77	69.79
▷ *(+Temperature Scaling)*	4.34	**19.73**	73.40	4.88	21.87	68.49	6.05	14.47	74.98	5.46	**16.36**	70.45
▷ *(+Isotonic Regression)*	**3.09**	20.51	69.13	**3.45**	**21.46**	67.10	**5.79**	14.53	73.70	**4.80**	16.73	68.40

Table 2: Calibration results for **LLaMA3** and **Aya** on MMMLU (left) and the Belebele subset (right). † denote methods that do not assume access to language identity. ‡ denote methods with given language identity. Indented italic rows correspond to post-hoc calibration adjustments.

Classical post-hoc methods offer improvements but face challenges in multilingual settings. Temperature scaling and isotonic regression noticeably reduce the calibration error for Aya (systematically overconfident, see Figure 2; Aya has 76.9% average confidence on MMMLU and 82.5% on Belebele). In this setting, flattening the confidence curve provides clear gains. However, these methods offer marginal benefit or even degradation for LLaMA3 (Avg. Conf. = 36.0% for MMMLU and 58.3% for Belebele), suggesting a global temperature fitted on the multilingual validation set might limited little benefit for individual languages due to distributional heterogeneity (see Simpson [1951]'s paradox). More broadly, while such methods adjust prediction confidence through global rescaling, they often struggle to deliver consistent improvements across languages and model families. This calls for finer-grained strategies or more structurally integrated calibration methods [Hébert-Johnson et al., 2018].

LACE is complementary to post-hoc approaches and delivers the best calibration performance. Importantly, our method *reshapes*, rather than *rescales*, the calibration signal (e.g., LLaMA3 baseline Avg. Conf=35.97% v.s. LACE Avg. Conf=36.57%). Therefore, our method does not compete with post-hoc calibrators but provides orthogonal improvements. As shown in Table 2, all methods combined with temperature scaling or isotonic regression yields further incremental gains, and notably LACE is further boosted to consistently deliver the lowest calibration error across benchmarks: ECE to 3.09 on LLaMA3 and 3.45 on Aya. This complementarity highlights the practical value of our approach as a flexible, additive pathway toward reliable multilingual calibration.

6 Conclusion

In this work, we present the first systematic studies of multilingual calibration in large language models. Our findings highlight stark disparities between English and other languages: models exhibit not only lower accuracy outside English but also severe miscalibration. Our analysis reveals that calibration quality is not uniform across depth: while English benefits from final-layer confidence signals, multilingual reliability emerges more strongly in intermediate representations. Building on this insight, we propose a family of training-free calibration methods that leverage these intermediate layers. We introduce the adaptive *LACE* method and demonstrate consistent, substantial improvements in multilingual calibration. Moreover, we show that these methods complement traditional post-hoc techniques, enabling state-of-the-art calibration. We hope this work motivates future research at the intersection of multilinguality and calibration and ultimately contributes to more equitable and trustworthy deployment of language technologies worldwide.

Ethics Statement

Our research adheres to strict ethical guidelines. We verified the licenses of all software and datasets used in this study to ensure full compliance with their terms. No privacy concerns have been identified. We have conducted a thorough assessment of the project and do not anticipate any further risks. We only use LLMs for grammar checking during the paper writing.

References

Marah Abdin, Jyoti Aneja, Harkirat Behl, Sébastien Bubeck, Ronen Eldan, Suriya Gunasekar, Michael Harrison, Russell J. Hewett, Mojan Javaheripi, Piero Kauffmann, James R. Lee, Yin Tat Lee, Yuanzhi Li, Weishung Liu, Caio C. T. Mendes, Anh Nguyen, Eric Price, Gustavo de Rosa, Olli Saarikivi, Adil Salim, Shital Shah, Xin Wang, Rachel Ward, Yue Wu, Dingli Yu, Cyril Zhang, and Yi Zhang. Phi-4 technical report, 2024. URL https://arxiv.org/abs/2412.08905.

Kabir Ahuja, Sunayana Sitaram, Sandipan Dandapat, and Monojit Choudhury. On the calibration of massively multilingual language models. In Yoav Goldberg, Zornitsa Kozareva, and Yue Zhang, editors, *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 4310–4323, Abu Dhabi, United Arab Emirates, December 2022. Association for Computational Linguistics. doi: 10.18653/v1/2022.emnlp-main.290. URL https://aclanthology.org/2022.emnlp-main.290/.

Jesujoba Alabi, Marius Mosbach, Matan Eyal, Dietrich Klakow, and Mor Geva. The hidden space of transformer language adapters. In Lun-Wei Ku, Andre Martins, and Vivek Srikumar, editors, *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 6588–6607, Bangkok, Thailand, August 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.acl-long.356. URL https://aclanthology.org/2024.acl-long.356/.

Lucas Bandarkar, Davis Liang, Benjamin Muller, Mikel Artetxe, Satya Narayan Shukla, Donald Husa, Naman Goyal, Abhinandan Krishnan, Luke Zettlemoyer, and Madian Khabsa. The belebele benchmark: a parallel reading comprehension dataset in 122 language variants. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, page 749–775. Association for Computational Linguistics, 2024a. doi: 10.18653/v1/2024.acl-long.44. URL http://dx.doi.org/10.18653/v1/2024.acl-long.44.

Lucas Bandarkar, Benjamin Muller, Pritish Yuvraj, Rui Hou, Nayan Singhal, Hongjiang Lv, and Bing Liu. Layer swapping for zero-shot cross-lingual transfer in large language models. *ArXiv preprint*, abs/2410.01335, 2024b. URL https://arxiv.org/abs/2410.01335.

Glenn W Brier. Verification of forecasts expressed in terms of probability. *Monthly weather review*, 78(1):1–3, 1950.

Alex Carriero, Kim Luijken, Anne de Hond, Karel GM Moons, Ben van Calster, and Maarten van Smeden. The harms of class imbalance corrections for machine learning based prediction models: a simulation study, 2024. URL https://arxiv.org/abs/2404.19494.

Prateek Chhikara. Mind the confidence gap: Overconfidence, calibration, and distractor effects in large language models, 2025. URL https://arxiv.org/abs/2502.11028.

Rochelle Choenni, Sara Rajaee, Christof Monz, and Ekaterina Shutova. On the evaluation practices in multilingual nlp: Can machine translation offer an alternative to human translations?, 2024.

Common Crawl Foundation. Common Crawl. https://commoncrawl.org, 2025. Accessed: 2025-07-26.

John Dang, Shivalika Singh, Daniel D'souza, Arash Ahmadian, Alejandro Salamanca, Madeline Smith, Aidan Peppin, Sungjin Hong, Manoj Govindassamy, Terrence Zhao, Sandra Kublik, Meor Amer, Viraat Aryabumi, Jon Ander Campos, Yi-Chern Tan, Tom Kocmi, Florian Strub, Nathan Grinsztajn, Yannis Flet-Berliac, Acyr Locatelli, Hangyu Lin, Dwarak Talupuru, Bharat Venkitesh, David Cairuz, Bowen Yang, Tim Chung, Wei-Yin Ko, Sylvie Shang Shi, Amir Shukayev, Sammie Bae, Aleksandra Piktus, Roman Castagné, Felipe Cruz-Salinas, Eddie Kim, Lucas Crawhall-Stein, Adrien Morisot, Sudip Roy, Phil Blunsom, Ivan Zhang, Aidan Gomez, Nick Frosst, Marzieh Fadaee, Beyza Ermis, Ahmet Üstün, and Sara Hooker. Aya expanse: Combining research breakthroughs for a new multilingual frontier, 2024. URL https://arxiv.org/abs/2412.04261.

DeepSeek-AI. Deepseek-r1: Incentivizing reasoning capability in llms via reinforcement learning, 2025. URL https://arxiv.org/abs/2501.12948.

Maha Elbayad, Jiatao Gu, Edouard Grave, and Michael Auli. Depth-adaptive transformer. In *8th International Conference on Learning Representations, ICLR 2020, Addis Ababa, Ethiopia, April 26-30, 2020*. OpenReview.net, 2020. URL https://openreview.net/forum?id=SJg7KhVKPH.

Tom Fawcett. An introduction to roc analysis. *Pattern Recognition Letters*, 27(8):861–874, 2006. ISSN 0167-8655. doi: https://doi.org/10.1016/j.patrec.2005.10.010. URL https://www.sciencedirect.com/science/article/pii/S016786550500303X. ROC Analysis in Pattern Recognition.

Riqiang Gao, Thomas Li, Yucheng Tang, Zhoubing Xu, Michael Kammer, Sanja L. Antic, Kim Sandler, Fabien Moldonado, Thomas A. Lasko, and Bennett Landman. A comparative study of confidence calibration in deep learning: From computer vision to medical imaging, 2022. URL https://arxiv.org/abs/2206.08833.

Jiahui Geng, Fengyu Cai, Yuxia Wang, Heinz Koeppl, Preslav Nakov, and Iryna Gurevych. A survey of confidence estimation and calibration in large language models. In Kevin Duh, Helena Gomez, and Steven Bethard, editors, *Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers)*, pages 6577–6595, Mexico City, Mexico, June 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.naacl-long.366. URL https://aclanthology.org/2024.naacl-long.366/.

Aaron Grattafiori, Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ahmad Al-Dahle, Aiesha Letman, Akhil Mathur, Alan Schelten, Alex Vaughan, et al. The llama 3 herd of models. *ArXiv preprint*, abs/2407.21783, 2024. URL https://arxiv.org/abs/2407.21783.

Chuan Guo, Geoff Pleiss, Yu Sun, and Kilian Q. Weinberger. On calibration of modern neural networks. In Doina Precup and Yee Whye Teh, editors, *Proceedings of the 34th International Conference on Machine Learning, ICML 2017, Sydney, NSW, Australia, 6-11 August 2017*, volume 70 of *Proceedings of Machine Learning Research*, pages 1321–1330. PMLR, 2017. URL http://proceedings.mlr.press/v70/guo17a.html.

Úrsula Hébert-Johnson, Michael P. Kim, Omer Reingold, and Guy N. Rothblum. Multicalibration: Calibration for the (computationally-identifiable) masses. In Jennifer G. Dy and Andreas Krause, editors, *Proceedings of the 35th International Conference on Machine Learning, ICML 2018, Stockholmsmässan, Stockholm, Sweden, July 10-15, 2018*, volume 80 of *Proceedings of Machine Learning Research*, pages 1944–1953. PMLR, 2018. URL http://proceedings.mlr.press/v80/hebert-johnson18a.html.

Dan Hendrycks, Collin Burns, Steven Basart, Andy Zou, Mantas Mazeika, Dawn Song, and Jacob Steinhardt. Measuring massive multitask language understanding. In *9th International Conference on Learning Representations, ICLR 2021, Virtual Event, Austria, May 3-7, 2021*. OpenReview.net, 2021. URL https://openreview.net/forum?id=d7KBjmI3GmQ.

Albert Q. Jiang, Alexandre Sablayrolles, Arthur Mensch, Chris Bamford, Devendra Singh Chaplot, Diego de las Casas, Florian Bressand, Gianna Lengyel, Guillaume Lample, Lucile Saulnier, Lélio Renard Lavaud, Marie-Anne Lachaux, Pierre Stock, Teven Le Scao, Thibaut Lavril, Thomas Wang, Timothée Lacroix, and William El Sayed. Mistral 7b, 2023. URL https://arxiv.org/abs/2310.06825.

Saurav Kadavath, Tom Conerly, Amanda Askell, Tom Henighan, Dawn Drain, Ethan Perez, Nicholas Schiefer, Zac Hatfield-Dodds, Nova DasSarma, Eli Tran-Johnson, Scott Johnston, Sheer El-Showk, Andy Jones, Nelson Elhage, Tristan Hume, Anna Chen, Yuntao Bai, Sam Bowman, Stanislav Fort, Deep Ganguli, Danny Hernandez, Josh Jacobson, Jackson Kernion, Shauna Kravec, Liane Lovitt, Kamal Ndousse, Catherine Olsson, Sam Ringer, Dario Amodei, Tom Brown, Jack Clark, Nicholas Joseph, Ben Mann, Sam McCandlish, Chris Olah, and Jared Kaplan. Language models (mostly) know what they know, 2022.

Takeshi Kojima, Itsuki Okimura, Yusuke Iwasawa, Hitomi Yanaka, and Yutaka Matsuo. On the multilingual ability of decoder-based pre-trained language models: Finding and controlling language-specific neurons. In Kevin Duh, Helena Gomez, and Steven Bethard, editors, *Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers)*, pages 6919–6971, Mexico City, Mexico, June 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.naacl-long.384. URL https://aclanthology.org/2024.naacl-long.384/.

Matthias Minderer, Josip Djolonga, Rob Romijnders, Frances Hubis, Xiaohua Zhai, Neil Houlsby, Dustin Tran, and Mario Lucic. Revisiting the calibration of modern neural networks. In Marc'Aurelio Ranzato, Alina Beygelzimer, Yann N. Dauphin, Percy Liang, and Jennifer Wortman Vaughan, editors, *Advances in Neural Information Processing Systems 34: Annual Conference on Neural Information Processing Systems 2021, NeurIPS 2021, December 6-14, 2021, virtual*, pages 15682–15694, 2021. URL https://proceedings.neurips.cc/paper/2021/hash/8420d359404024567b5aefda1231af24-Abstract.html.

Libo Qin, Qiguang Chen, Yuhang Zhou, Zhi Chen, Yinghui Li, Lizi Liao, Min Li, Wanxiang Che, and Philip S Yu. A survey of multilingual large language models. *Patterns*, 6(1), 2025.

Sebastian Ruder, Ivan Vulić, and Anders Søgaard. Square one bias in NLP: Towards a multi-dimensional exploration of the research manifold. In Smaranda Muresan, Preslav Nakov, and Aline Villavicencio, editors, *Findings of the Association for Computational Linguistics: ACL 2022*, pages 2340–2354, Dublin, Ireland, May 2022. Association for Computational Linguistics. doi: 10.18653/v1/2022.findings-acl.184. URL https://aclanthology.org/2022.findings-acl.184/.

Freda Shi, Mirac Suzgun, Markus Freitag, Xuezhi Wang, Suraj Srivats, Soroush Vosoughi, Hyung Won Chung, Yi Tay, Sebastian Ruder, Denny Zhou, Dipanjan Das, and Jason Wei. Language models are multilingual chain-of-thought reasoners. In *The Eleventh International Conference on Learning Representations, ICLR 2023, Kigali, Rwanda, May 1-5, 2023*. OpenReview.net, 2023. URL https://openreview.net/pdf?id=fR3wGCk-IXp.

E. H. Simpson. The interpretation of interaction in contingency tables. *Journal of the Royal Statistical Society: Series B (Methodological)*, 13(2):238–241, 1951. doi: https://doi.org/10.1111/j.2517-6161.1951.tb00088.x. URL https://rss.onlinelibrary.wiley.com/doi/abs/10.1111/j.2517-6161.1951.tb00088.x.

Ian Tenney, Dipanjan Das, and Ellie Pavlick. BERT rediscovers the classical NLP pipeline. In Anna Korhonen, David Traum, and Lluís Màrquez, editors, *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 4593–4601, Florence, Italy, 2019. Association for Computational Linguistics. doi: 10.18653/v1/P19-1452. URL https://aclanthology.org/P19-1452.

Eva Vanmassenhove, Dimitar Shterionov, and Matthew Gwilliam. Machine translationese: Effects of algorithmic bias on linguistic complexity in machine translation. In Paola Merlo, Jorg Tiedemann, and Reut Tsarfaty, editors, *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*, pages 2203–2213, Online, April 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.eacl-main.188. URL https://aclanthology.org/2021.eacl-main.188/.

Chris Wendler, Veniamin Veselovsky, Giovanni Monea, and Robert West. Do llamas work in English? on the latent language of multilingual transformers. In Lun-Wei Ku, Andre Martins, and Vivek Srikumar, editors, *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 15366–15394, Bangkok, Thailand, August 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.acl-long.820. URL https://aclanthology.org/2024.acl-long.820/.

Miao Xiong, Zhiyuan Hu, Xinyang Lu, Yifei Li, Jie Fu, Junxian He, and Bryan Hooi. Can llms express their uncertainty? an empirical evaluation of confidence elicitation in llms. In *The Twelfth International Conference on Learning Representations, ICLR 2024, Vienna, Austria, May 7-11, 2024*. OpenReview.net, 2024. URL https://openreview.net/forum?id=gjeQKFxFpZ.

Boyang Xue, Hongru Wang, Rui Wang, Sheng Wang, Zezhong Wang, Yiming Du, Bin Liang, and Kam-Fai Wong. Mlingconf: A comprehensive study of multilingual confidence estimation on large language models. *ArXiv preprint*, abs/2410.12478, 2024. URL `https://arxiv.org/abs/2410.12478`.

An Yang, Baosong Yang, Binyuan Hui, Bo Zheng, Bowen Yu, Chang Zhou, Chengpeng Li, Chengyuan Li, Dayiheng Liu, Fei Huang, Guanting Dong, Haoran Wei, Huan Lin, Jialong Tang, Jialin Wang, Jian Yang, Jianhong Tu, Jianwei Zhang, Jianxin Ma, Jianxin Yang, Jin Xu, Jingren Zhou, Jinze Bai, Jinzheng He, Junyang Lin, Kai Dang, Keming Lu, Keqin Chen, Kexin Yang, Mei Li, Mingfeng Xue, Na Ni, Pei Zhang, Peng Wang, Ru Peng, Rui Men, Ruize Gao, Runji Lin, Shijie Wang, Shuai Bai, Sinan Tan, Tianhang Zhu, Tianhao Li, Tianyu Liu, Wenbin Ge, Xiaodong Deng, Xiaohuan Zhou, Xingzhang Ren, Xinyu Zhang, Xipin Wei, Xuancheng Ren, Xuejing Liu, Yang Fan, Yang Yao, Yichang Zhang, Yu Wan, Yunfei Chu, Yuqiong Liu, Zeyu Cui, Zhenru Zhang, Zhifang Guo, and Zhihao Fan. Qwen2 technical report, 2024a. URL `https://arxiv.org/abs/2407.10671`.

Ruihan Yang, Caiqi Zhang, Zhisong Zhang, Xinting Huang, Sen Yang, Nigel Collier, Dong Yu, and Deqing Yang. Logu: Long-form generation with uncertainty expressions, 2024b. URL `https://arxiv.org/abs/2410.14309`.

Ruihan Yang, Caiqi Zhang, Zhisong Zhang, Xinting Huang, Dong Yu, Nigel Collier, and Deqing Yang. Uncle: Uncertainty expressions in long-form generation, 2025.

Yahan Yang, Soham Dan, Dan Roth, and Insup Lee. On the calibration of multilingual question answering llms, 2023.

Bianca Zadrozny and Charles Elkan. Transforming classifier scores into accurate multiclass probability estimates. *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 2002. doi: 10.1145/775047.775151.

Caiqi Zhang, Zhijiang Guo, and Andreas Vlachos. Do we need language-specific fact-checking models? the case of Chinese. In Yaser Al-Onaizan, Mohit Bansal, and Yun-Nung Chen, editors, *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*, pages 1899–1914, Miami, Florida, USA, November 2024a. Association for Computational Linguistics. doi: 10.18653/v1/2024.emnlp-main.113. URL `https://aclanthology.org/2024.emnlp-main.113/`.

Caiqi Zhang, Fangyu Liu, Marco Basaldella, and Nigel Collier. LUQ: Long-text uncertainty quantification for LLMs. In Yaser Al-Onaizan, Mohit Bansal, and Yun-Nung Chen, editors, *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*, pages 5244–5262, Miami, Florida, USA, November 2024b. Association for Computational Linguistics. doi: 10.18653/v1/2024.emnlp-main.299. URL `https://aclanthology.org/2024.emnlp-main.299/`.

Caiqi Zhang, Ruihan Yang, Zhisong Zhang, Xinting Huang, Sen Yang, Dong Yu, and Nigel Collier. Atomic calibration of llms in long-form generations, 2024c.

Caiqi Zhang, Chang Shu, Ehsan Shareghi, and Nigel Collier. All roads lead to rome: Graph-based confidence estimation for large language model reasoning, 2025a.

Caiqi Zhang, Xiaochen Zhu, Chengzu Li, Nigel Collier, and Andreas Vlachos. Reinforcement learning for better verbalized confidence in long-form generation, 2025b.

Mozhi Zhang, Mianqiu Huang, Rundong Shi, Linsen Guo, Chong Peng, Peng Yan, Yaqian Zhou, and Xipeng Qiu. Calibrating the confidence of large language models by eliciting fidelity. In Yaser Al-Onaizan, Mohit Bansal, and Yun-Nung Chen, editors, *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*, pages 2959–2979, Miami, Florida, USA, November 2024d. Association for Computational Linguistics. doi: 10.18653/v1/2024.emnlp-main.173. URL `https://aclanthology.org/2024.emnlp-main.173/`.

Zhihan Zhang, Dong-Ho Lee, Yuwei Fang, Wenhao Yu, Mengzhao Jia, Meng Jiang, and Francesco Barbieri. PLUG: Leveraging pivot language in cross-lingual instruction tuning. In Lun-Wei Ku, Andre Martins, and Vivek Srikumar, editors, *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 7025–7046, Bangkok, Thailand, August 2024e. Association for Computational Linguistics. doi: 10.18653/v1/2024.acl-long.379. URL https://aclanthology.org/2024.acl-long.379/.

Ahmet Üstün, Viraat Aryabumi, Zheng-Xin Yong, Wei-Yin Ko, Daniel D'souza, Gbemileke Onilude, Neel Bhandari, Shivalika Singh, Hui-Lee Ooi, Amr Kayid, Freddie Vargus, Phil Blunsom, Shayne Longpre, Niklas Muennighoff, Marzieh Fadaee, Julia Kreutzer, and Sara Hooker. Aya model: An instruction finetuned open-access multilingual language model, 2024. URL https://arxiv.org/abs/2402.07827.

A Limitations

We conduct experiments on mid-scale models (7B–8B parameters), leaving larger model sizes out of the current picture; larger models may exhibit different internal dynamics. Further, our focus is on standard multiple-choice QA tasks as with such tasks model correctness is well-defined and easy to measure. The observed benefits of using intermediate layers may not directly extend to open-ended generative tasks such as dialogue, summarization, or long-form QA: we leave those tasks for future research. Finally, our proposed methods are post-hoc interventions that correct poor calibration, rather than fundamental solutions that integrate multilingual calibration objectives into the model's training process to address the issue at its root. This constitutes another very compelling direction for future research.

B Benchmarking Multilingual Calibration

In this section, we present the detailed multilingual evaluation results for the models and benchmarks discussed in the main text.

B.1 Models

Our experiments evaluate recent multilingual large language models:

- **LLaMA3** [Grattafiori et al., 2024] (`Llama-3.1-8B-Instruct`)
- **Qwen2.5** [Yang et al., 2024a] (`Qwen2.5-7B-Instruct`)
- **Mistral** [Jiang et al., 2023] (`Mistral-7B-Instruct-v0.3`)
- **Aya** [Dang et al., 2024] (`aya-expanse-8b`)
- **DeepSeek** [DeepSeek-AI, 2025] (`DeepSeek-R1-Distill-Qwen-7B`)
- **Phi** [Abdin et al., 2024] (`phi-4`)

B.2 MMMLU Results

Language	AUROC	ECE	BRIER	Accuracy
Arabic	64.91	41.18	11.87	4.50
Bengali	64.56	49.70	11.72	0.10
German	70.84	24.14	29.32	43.00
English	73.75	23.92	27.95	54.00
Spanish	71.33	21.64	26.79	42.90
French	71.25	22.20	28.36	46.40
Hindi	75.08	39.77	6.23	1.60
Indonesian	69.48	26.98	29.69	38.80
Italian	74.08	25.24	28.25	44.50
Japanese	56.09	44.15	15.48	6.50
Korean	39.78	46.62	16.25	5.50
Portuguese	71.11	29.25	27.59	47.10
Swahili	56.02	30.81	27.34	26.30
Yoruba	44.79	44.18	21.99	16.10
Chinese	62.12	33.55	24.58	16.70
Avg. Low-Resource	62.47	38.77	18.14	14.57
Avg. High-Resource	65.59	30.08	24.95	34.07
Avg. Latin-Script	71.69	24.77	28.28	45.24
Avg. Non-Latin-Script	57.92	41.24	16.93	9.66
Average (All Languages)	**64.35**	**33.56**	**22.23**	**26.27**

Table 3: Performance comparison across languages for AUROC, ECE, BRIER score, and Accuracy in **Mistral**, evaluated on the MMMLU dataset.

Results for each model are reported in the following tables: Mistral (Table 3), Qwen2.5 (Table 4), Phi (Table 5), and DeepSeek (Table 6).

Language	AUROC	ECE	BRIER	Accuracy
Arabic	67.15	14.30	26.67	54.90
Bengali	64.10	26.68	31.98	33.20
German	76.94	21.59	25.08	55.60
English	78.23	15.77	19.25	65.60
Spanish	76.95	19.26	23.98	61.10
French	75.65	16.92	22.88	62.20
Hindi	72.01	28.73	28.86	33.90
Indonesian	75.69	15.83	23.53	54.30
Italian	75.32	21.07	24.46	58.70
Japanese	80.03	6.71	17.10	33.10
Korean	74.15	17.60	25.75	52.20
Portuguese	75.85	18.86	23.61	58.40
Swahili	59.93	30.12	33.09	32.30
Yoruba	23.49	46.99	36.11	2.00
Chinese	85.31	12.47	17.42	47.00
Avg. Low-Resource	60.40	27.11	30.04	35.10
Avg. High-Resource	77.60	16.69	22.17	54.88
Avg. Latin-Script	76.38	18.47	23.26	59.41
Avg. Non-Latin-Script	65.77	22.95	27.12	36.08
Average (All Languages)	**70.72**	**20.86**	**25.32**	**46.97**

Table 4: Performance comparison across languages for AUROC, ECE, BRIER score, and Accuracy in **Qwen 2.5**, evaluated on the MMMLU dataset.

Language	AUROC	ECE	BRIER	Accuracy
Arabic	52.66	30.21	25.35	36.50
Bengali	52.62	34.13	24.73	27.20
German	63.47	22.86	22.86	65.60
English	71.13	20.48	17.92	73.10
Spanish	61.29	27.15	25.32	56.40
French	71.57	17.07	20.21	68.90
Hindi	37.74	46.43	26.16	15.70
Indonesian	42.89	32.36	30.63	30.70
Italian	72.25	10.51	19.13	67.50
Japanese	30.62	46.69	17.59	8.30
Korean	66.95	29.00	24.50	50.00
Portuguese	73.79	13.24	18.77	66.60
Swahili	64.42	16.18	23.61	40.50
Yoruba	53.76	20.83	21.01	27.60
Chinese	59.73	31.98	26.17	44.60
Avg. Low-Resource	50.68	30.02	25.25	29.70
Avg. High-Resource	63.42	24.33	21.39	55.67
Avg. Latin-Script	65.20	20.52	22.12	61.26
Avg. Non-Latin-Script	52.31	31.93	23.64	31.30
Average (All Languages)	**58.33**	**26.61**	**22.93**	**45.28**

Table 5: Performance comparison across languages for AUROC, ECE, BRIER score, and Accuracy in **Phi**, evaluated on the MMMLU dataset.

B.3 MMMLU Language Group Definitions

We randomly sampled 1,000 examples per language for MMMLU. We group languages in the MMLU dataset according to resource availability and script as follows:

Low-Resource Languages Languages with relatively limited annotated data and pretrained model support: Arabic, Bengali, Swahili, Yoruba, Hindi, Indonesian.

Language	AUROC	ECE	BRIER	Accuracy
Arabic	55.33	32.74	21.54	26.40
Bengali	58.50	40.80	14.41	13.70
German	60.28	18.50	23.91	39.80
English	66.21	9.10	22.92	47.10
Spanish	62.24	12.47	23.51	40.80
French	62.93	10.84	23.12	41.40
Hindi	56.08	30.42	20.62	26.40
Indonesian	61.00	31.61	21.11	27.30
Italian	63.14	5.65	22.85	40.40
Japanese	55.56	18.05	23.14	32.10
Korean	21.56	49.09	18.66	1.10
Portuguese	62.37	16.78	23.26	39.10
Swahili	51.67	45.76	12.45	12.00
Yoruba	60.35	38.16	4.94	2.80
Chinese	69.00	16.13	23.97	43.10
Avg. Low-Resource	57.16	36.58	15.84	18.10
Avg. High-Resource	58.14	17.40	22.82	36.10
Avg. Latin-Script	62.60	14.99	22.95	39.41
Avg. Non-Latin-Script	53.51	33.89	17.47	19.70
Average (All Languages)	**57.75**	**25.07**	**20.03**	**28.90**

Table 6: Performance comparison across languages for AUROC, ECE, BRIER score, and Accuracy in **DeepSeek**, evaluated on the MMMLU dataset.

High-Resource Languages Languages with substantial resources and strong support in major multilingual models: German, French, English, Spanish, Chinese, Italian, Japanese, Korean, Portuguese.

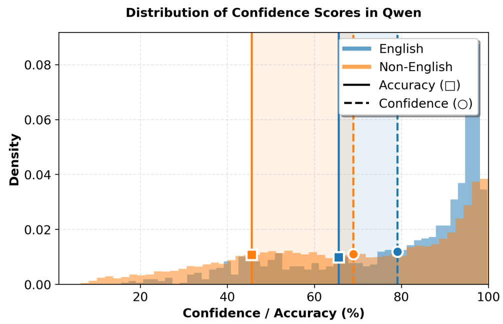
Latin-Script Languages Languages primarily written using the Latin script: German, English, Spanish, French, Indonesian, Italian, Portuguese.

Non-Latin-Script Languages Languages primarily written using non-Latin scripts (e.g., Arabic script, Devanagari, Hangul, Han characters): Arabic, Bengali, Hindi, Japanese, Korean, Swahili, Yoruba, Chinese.

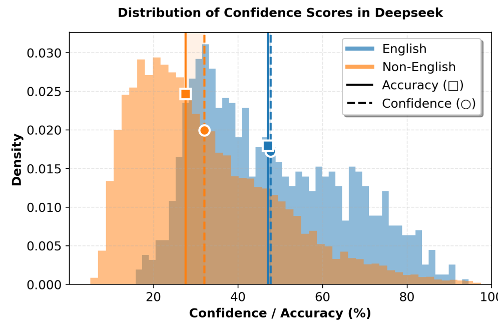
B.4 Model Confidence Behaviours

Figure 6 illustrates the distribution of confidence scores and accuracies across English and non-English settings for Qwen2.5, DeepSeek, Mistral, and Phi. Solid vertical lines indicate mean accuracies, while dashed vertical lines indicate mean confidences. The divergence between confidence and accuracy highlights calibration behaviour: underconfidence when the dashed line falls left of the solid line, and overconfidence when it falls to the right.

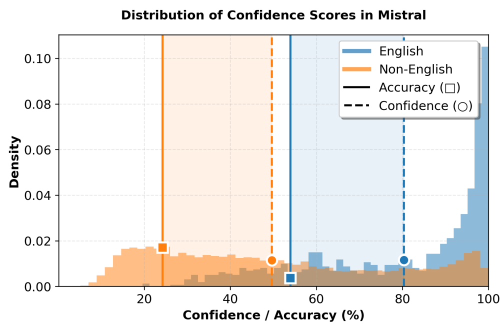
Table 7 reports detailed calibration and confidence statistics for LLaMA3. In addition to standard accuracy, we provide the model's average confidence, the confidence gap (accuracy minus confidence), the proportion of correct predictions made with low confidence ("Underconf"), and the mean confidence levels assigned to correct vs. incorrect predictions. We further include the difference between these two distributions ("Corr–Inc Gap"), which captures how well the model separates correct from incorrect responses. English shows a relatively small confidence gap (2.5%), with strong separation between correct and incorrect predictions (23.8% Corr–Inc Gap). In contrast, most non-English languages show lower accuracy, larger underconfidence rates, and much smaller separation between correct and incorrect predictions (average Corr–Inc Gap of 6.3%).



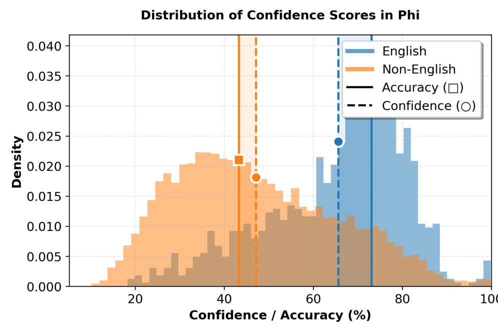
(a) Qwen 2.5



(b) DeepSeek



(c) Mistral



(d) Phi

Figure 6: Distribution of confidence scores (predicted probabilities) versus accuracies in English (blue) and non-English (orange) for four models: (a) Qwen 2.5, (b) DeepSeek, (c) Mistral, and (d) Phi.

Language	Acc. (%)	Avg Conf (%)	Conf Gap (%)	Underconf (%)	Corr. Conf (%)	Inc. Conf (%)	Corr–Inc Gap (%)
Arabic	38.2	29.5	8.8	89.0	31.7	28.0	3.7
Chinese	23.1	23.2	-0.1	99.6	22.2	23.6	-1.4
Korean	42.5	31.2	11.3	92.0	33.5	29.5	4.0
Japanese	43.0	24.0	19.0	92.3	26.8	21.8	5.0
Swahili	32.2	31.5	0.7	88.8	34.2	30.3	3.9
Italian	51.8	41.8	10.0	58.3	47.4	35.8	11.6
Bengali	35.2	34.6	0.6	88.4	36.1	33.8	2.3
Spanish	52.0	46.1	5.9	50.0	52.6	39.0	13.6
Portuguese	50.4	47.1	3.3	47.0	53.6	40.6	13.0
Indonesian	45.0	37.0	8.0	75.3	41.1	33.7	7.4
Hindi	39.9	31.7	8.2	88.2	34.1	30.1	4.0
German	44.4	33.8	10.6	80.4	37.1	31.2	5.9
Yoruba	27.4	29.4	-2.0	93.8	31.5	28.7	2.8
French	51.3	41.5	9.8	59.5	47.4	35.3	12.1
English	61.2	58.8	2.5	**25.7**	68.0	44.2	**23.8**
Non-English	41.2	34.5	6.7	**78.8**	37.8	31.5	**6.3**

Table 7: LLaMA3 Calibration and underconfidence analysis across languages. Metrics include accuracy, average confidence, confidence gap (accuracy minus confidence), proportion of underconfident correct predictions (confidence $<$ 0.5 when correct), average confidence for correct vs. incorrect predictions, and their difference (Corr–Inc Gap).

B.5 Belebele Results

Belebele [Bandarkar et al., 2024a] is a multiple-choice dataset covering 122 language variants, enabling robust evaluation of NLU across high-, medium-, and low-resource languages. The dataset is fully parallel, allowing for direct cross-linguistic comparison of model performance. In our experiments, we sample 400 examples per language and evaluate the six model.

Language Code The following FLORES-200 language codes (3-letter form) are included in the dataset evaluation:

acm - Mesopotamian Arabic
afr - Afrikaans
als - Tosk Albanian
amh - Amharic
apc - North Levantine Arabic
arb - Modern Standard Arabic
ars - Najdi Arabic
ary - Moroccan Arabic
arz - Egyptian Arabic
asm - Assamese
azj - North Azerbaijani
bam - Bambara
ben - Bengali
bod - Standard Tibetan
bul - Bulgarian
cat - Catalan
ceb - Cebuano
ces - Czech
ckb - Central Kurdish
dan - Danish
deu - German
ell - Greek
eng - English
est - Estonian
eus - Basque
fin - Finnish
fra - French
fuv - Nigerian Fulfulde
gaz - West Central Oromo
grn - Guarani
guj - Gujarati
hat - Haitian Creole
hau - Hausa
heb - Hebrew
hin - Hindi
hrv - Croatian
hun - Hungarian
hye - Armenian
ibo - Igbo
ilo - Ilocano
ind - Indonesian
isl - Icelandic
ita - Italian
jav - Javanese
jpn - Japanese
kac - Jingpho
kan - Kannada
kat - Georgian
kaz - Kazakh
kea - Kabuverdianu
khk - Halh Mongolian
khm - Khmer
kin - Kinyarwanda
kir - Kyrgyz
kor - Korean
lao - Lao
lin - Lingala
lit - Lithuanian
lug - Ganda
luo - Luo
lvs - Standard Latvian
mal - Malayalam
mar - Marathi
mkd - Macedonian
mlt - Maltese
mri - Maori
mya - Burmese
nld - Dutch
nob - Norwegian Bokmål
npi - Nepali
nso - Northern Sotho
nya - Nyanja
ory - Odia
pan - Eastern Panjabi
pbt - Southern Pashto
pes - Western Persian
plt - Plateau Malagasy
pol - Polish
por - Portuguese
ron - Romanian
rus - Russian
shn - Shan
sin - Sinhala
slk - Slovak
slv - Slovenian
sna - Shona
snd - Sindhi
som - Somali
sot - Southern Sotho
spa - Spanish
srp - Serbian
ssw - Swati
sun - Sundanese
swe - Swedish
swh - Swahili
tam - Tamil
tel - Telugu
tgk - Tajik
tgl - Tagalog
tha - Thai
tir - Tigrinya
tsn - Tswana
tso - Tsonga
tur - Turkish
ukr - Ukrainian
urd - Urdu
uzn - Northern Uzbek
vie - Vietnamese
war - Waray
wol - Wolof
xho - Xhosa
yor - Yoruba
zho - Chinese
zsm - Standard Malay
zul - Zulu

Set 1					Set 2					Set 3				
Lang	**Acc**	**AUR.**	**ECE**	**Brier**	**Lang**	**Acc**	**AUR.**	**ECE**	**Brier**	**Lang**	**Acc**	**AUR.**	**ECE**	**Brier**
acm	58.2	78.4	7.1	19.2	arz	69.8	77.8	12.2	18.2	ceb	65.8	75.6	11.1	19.7
fin	80.8	75.6	6.0	14.1	hin	67.0	72.9	14.0	20.6	ita	86.0	79.6	7.4	10.8
khm	4.0	5.5	66.2	51.4	lvs	74.8	79.7	11.3	16.2	npi	59.8	74.8	5.1	20.0
pol	80.0	78.9	6.3	13.3	slv	81.0	76.6	8.7	13.8	swe	79.2	81.6	7.3	12.8
tso	34.0	62.5	3.4	21.5	xho	37.0	60.0	5.0	22.8	afr	80.8	81.2	8.3	12.7
asm	45.8	68.0	6.1	22.8	ces	82.2	80.2	7.8	11.8	fra	86.2	77.4	9.9	11.4
hin	57.0	72.1	4.7	21.1	jav	68.0	78.4	11.1	18.4	kin	34.8	63.3	4.7	21.3
mal	60.5	74.0	12.3	21.3	npi	32.5	59.9	6.3	21.4	por	86.2	79.8	5.6	10.2
sna	35.8	58.6	6.2	23.0	swh	67.0	75.0	8.1	19.1	tur	78.2	78.8	8.5	14.6
yor	31.2	61.1	4.4	20.4	als	73.5	78.0	7.2	16.2	azj	66.8	71.8	14.3	21.4
ckb	46.0	71.8	8.3	22.2	fuv	28.0	51.9	5.2	20.4	hrv	79.8	78.1	8.2	14.3
jpn	66.5	73.3	29.9	28.0	kir	63.0	73.8	21.9	24.7	mar	67.5	73.5	9.2	19.4
nso	37.8	60.3	3.2	22.7	snd	17.5	50.5	30.0	25.3	tam	65.5	73.4	14.5	21.5
ukr	84.2	77.4	12.1	12.8	zho	76.5	71.2	30.6	25.2	amh	34.8	63.2	5.0	21.5
bam	31.2	60.6	4.8	20.8	dan	79.8	78.8	8.2	13.9	gaz	31.8	53.1	2.4	21.7
hun	82.5	84.0	9.7	11.8	kac	30.2	61.8	3.5	20.5	kor	77.8	77.9	14.5	16.3
mkd	77.8	79.1	7.8	14.4	nya	32.0	60.7	3.3	21.1	ron	80.0	80.4	6.3	13.0
som	35.2	59.0	3.9	22.2	tel	59.5	73.7	7.2	20.4	urd	59.5	67.3	19.7	25.8
zho	81.2	68.9	24.4	21.1	apc	65.0	78.3	9.7	18.4	ben	65.5	72.6	10.1	20.3
deu	86.8	72.3	13.4	12.9	grn	39.8	65.5	6.6	22.4	hye	0.2	1.5	63.8	42.1
kan	58.5	72.1	5.2	20.9	lao	32.5	59.5	2.1	21.5	mlt	69.8	76.4	9.9	18.4
ory	55.8	70.0	16.4	24.7	rus	81.2	81.0	10.4	13.0	sot	32.8	57.5	2.6	21.8
tgk	63.8	70.1	12.5	22.1	urd	41.2	64.8	4.3	22.5	zsm	82.5	82.9	9.5	11.8
arb	79.5	74.2	11.8	15.5	ben	35.2	59.9	4.9	22.4	ell	80.5	80.6	10.1	13.7
guj	58.0	68.8	8.2	22.0	ibo	40.2	62.0	3.7	22.6	kat	1.5	6.0	68.4	51.6
lin	34.2	59.3	3.5	21.9	mri	35.5	63.3	4.3	21.5	pan	58.0	74.4	11.4	21.6
shn	16.8	47.9	15.1	16.9	spa	84.0	79.3	5.8	11.7	tgl	75.2	80.1	7.8	15.3
uzn	69.0	77.0	13.4	19.2	zul	36.5	59.3	5.1	22.8	arb	29.8	56.4	3.6	20.8
bod	29.0	60.2	6.8	20.3	sun	65.5	74.3	13.5	20.9	hat	55.8	72.9	4.6	20.9
ilo	54.0	69.8	9.2	22.6	kaz	63.5	75.6	19.3	23.0	lit	73.8	82.3	11.0	15.7
mya	0.8	7.2	72.5	55.7	pbt	47.5	67.7	3.1	22.6	sin	32.2	59.2	3.8	21.5
srp	83.2	77.5	13.0	13.7	tha	71.8	75.5	19.8	21.2	vie	83.5	78.4	8.7	12.4
ars	62.0	78.5	9.6	18.8	bul	80.8	77.7	13.6	14.6	est	71.8	78.2	4.2	16.4
hau	45.2	67.1	11.7	23.9	ind	81.8	75.6	6.4	13.4	kea	48.8	73.0	8.0	21.1
lug	35.5	57.6	2.5	22.5	nld	83.0	78.2	5.9	12.0	pes	79.2	77.8	8.5	14.4
sin	58.8	72.7	10.3	21.6	ssw	31.8	61.5	3.0	20.8	tir	28.0	57.7	4.9	19.7
war	62.2	74.7	12.1	21.0	ary	58.5	72.0	7.7	21.2	cat	86.2	84.8	9.4	10.2
eus	69.5	75.7	7.0	18.1	heb	77.2	76.9	17.2	17.8	isl	67.0	78.3	5.2	17.4
khk	48.0	70.2	10.0	22.9	luo	31.8	55.7	5.7	21.5	nob	79.2	77.8	9.5	14.7
plt	44.2	65.6	5.8	23.1	slk	82.0	76.9	4.7	13.0	**eng**	**87.8**	**87.9**	**4.0**	**8.1**
tsn	31.8	62.7	4.6	20.8	wol	33.0	53.2	5.7	22.3	**Avg.**	**57.6**	**68.9**	**10.9**	**19.8**

Table 8: Per-language performance on the belebele test set for the **LLaMA3** model, reporting AUROC, ECE, and Brier score. Each row is color-coded by language category, based on resource availability (high, medium, low) and script type (Latin vs. non-Latin). The categories are shaded with soft pastel colors: high-resource Latin (light blue), high-resource non-Latin (light pink), medium-resource Latin (light green), medium-resource non-Latin (lavender), low-resource Latin (cream), and low-resource non-Latin (tan). English line and the Average line is **bolded**.

	Set 1					Set 2					Set 3			
Lang	**Acc**	**AUR.**	**ECE**	**Brier**	**Lang**	**Acc**	**AUR.**	**ECE**	**Brier**	**Lang**	**Acc**	**AUR.**	**ECE**	**Brier**
acm	64.7	77.4	25.6	26.8	arz	75.7	82.3	16.7	17.5	ceb	47.3	72.9	29.9	30.7
fin	63.0	64.7	17.1	25.2	hin	67.3	75.0	22.7	24.1	ita	80.3	80.1	12.7	14.4
lvs	55.3	68.6	24.1	28.4	npi	43.3	67.7	32.7	33.4	pol	79.7	80.0	14.5	16.1
slv	63.3	75.4	23.5	25.9	swe	74.3	69.2	18.5	20.8	tso	34.3	57.7	29.4	32.3
xho	34.0	59.0	25.2	29.4	afr	71.0	80.5	18.7	20.1	asm	38.3	59.8	25.7	30.2
ces	80.7	81.5	13.4	14.2	fra	86.7	82.0	8.5	10.3	hin	54.0	68.5	28.6	30.4
jav	56.7	75.5	25.2	26.6	kin	36.7	58.0	26.8	30.7	npi	37.3	61.7	28.9	31.7
por	83.0	79.0	12.2	12.9	sna	34.0	66.5	28.5	29.1	swh	37.0	66.9	32.2	32.1
tur	78.3	82.0	12.9	15.6	yor	29.7	53.6	29.6	31.8	als	49.0	69.7	26.4	29.6
azj	58.7	67.0	18.4	26.0	ckb	47.0	63.6	29.4	33.0	fuv	27.7	54.9	34.1	34.0
hrv	68.0	76.6	21.4	23.1	jpn	78.3	75.8	13.1	16.1	kir	44.7	63.3	32.8	34.6
mar	45.3	66.6	32.3	33.9	nso	34.7	58.0	27.8	31.4	snd	40.7	62.8	22.8	28.6
tam	28.3	54.9	32.6	33.4	ukr	81.3	83.5	13.0	14.0	zho	84.3	86.8	8.6	10.6
amh	26.0	48.2	16.9	23.8	bam	35.3	62.1	25.8	29.2	dan	72.0	77.2	14.1	18.4
gaz	32.3	51.2	26.1	30.8	hun	60.0	72.2	23.7	26.2	kac	33.0	63.2	23.9	27.2
kor	78.7	77.2	14.7	15.8	mkd	61.0	74.9	22.7	25.1	nya	33.7	54.6	25.7	31.0
ron	82.0	82.7	12.8	13.5	som	33.0	63.9	29.7	30.6	urd	50.3	68.9	16.1	25.1
zho	80.3	76.2	11.6	14.9	apc	67.7	78.7	20.9	21.6	ben	49.7	65.0	20.7	28.1
deu	83.3	77.7	12.2	13.6	grn	35.7	64.7	31.9	32.3	hye	36.7	57.6	21.9	28.5
mlt	41.3	65.6	29.1	31.7	rus	83.3	82.0	12.4	13.3	sot	33.7	55.2	27.1	31.6
tgk	38.7	68.5	23.7	27.3	urd	41.3	63.0	26.0	30.9	zsm	79.7	81.3	12.3	14.4
arb	80.0	78.9	14.8	15.3	ben	36.0	62.8	29.3	31.5	ell	81.7	84.9	10.1	12.7
wol	31.6	56.5	22.0	27.7	ibo	30.0	50.7	27.4	31.9	kat	46.7	64.8	26.8	30.1
lin	33.0	63.0	34.9	34.2	mri	35.3	60.0	26.7	30.2	spa	79.0	78.2	19.1	18.3
tgl	69.0	73.6	17.5	21.6	uzn	46.9	66.0	29.1	32.3	zul	31.1	58.1	25.6	28.7
arb	28.3	54.7	33.8	34.0	plt	35.2	58.9	21.5	27.2	hat	46.4	67.9	27.2	30.3
ilo	37.8	68.2	30.7	31.1	kaz	42.1	67.3	30.4	32.3	lit	63.5	74.2	23.5	25.8
pbt	36.0	60.6	31.6	33.3	sin	36.0	58.2	23.0	29.0	srp	66.1	71.9	17.8	23.3
tha	49.0	69.2	24.9	28.7	vie	82.7	80.8	10.7	12.8	ars	65.6	78.3	25.7	25.6
bul	67.6	77.4	21.8	23.4	est	51.8	67.8	25.1	29.4	hau	29.3	60.8	33.2	32.3
ind	80.6	81.0	13.8	14.9	kea	47.5	67.2	33.1	34.4	lug	31.1	55.8	23.6	27.9
nld	81.1	79.4	12.6	14.7	pes	80.1	78.7	12.4	15.0	tsn	33.7	60.9	23.3	28.0
ssw	36.2	55.7	21.1	29.0	tir	27.6	54.7	23.9	27.0	war	49.2	66.5	26.3	30.6
ary	64.3	77.2	24.2	25.4	cat	76.5	81.4	14.7	16.3	eus	47.2	64.8	22.6	29.1
heb	79.8	79.6	11.5	14.7	isl	51.5	70.9	27.0	29.6	khk	37.5	57.6	21.7	28.8
luo	29.1	63.9	26.3	26.5	nob	72.7	77.0	16.2	19.0	**eng**	**87.0**	**83.6**	**4.8**	**8.7**
slk	76.8	80.7	15.1	16.9	sun	47.5	74.6	30.9	30.9	**Avg.**	**53.0**	**68.0**	**22.8**	**25.2**

Table 9: Per-language performance on the belebele test set for the **Aya** model, reporting AUROC, ECE, and Brier score. Each row is color-coded, same as Table 8. Language entries with lower than 5% accuracy is excluded. English line and the Average line is **bolded**.

Set 1					Set 2					Set 3				
Lang	**Acc**	**AUR.**	**ECE**	**Brier**	**Lang**	**Acc**	**AUR.**	**ECE**	**Brier**	**Lang**	**Acc**	**AUR.**	**ECE**	**Brier**
acm	63.5	68.1	7.1	21.7	arz	72.2	77.2	7.1	16.6	ceb	52.8	74.2	17.2	23.6
fin	72.8	79.5	15.3	18.1	hin	67.5	68.1	9.2	20.8	ita	87.5	79.5	6.8	9.8
khm	10.8	57.5	21.5	15.0	lvs	73.5	71.5	10.7	18.1	npi	45.2	58.8	19.9	29.4
pol	81.8	82.8	9.0	12.2	slv	78.2	77.2	7.8	14.1	swe	83.8	76.8	8.0	12.3
tso	17.2	79.5	24.3	17.9	xho	34.8	57.0	27.5	31.4	afr	86.5	75.0	7.1	11.1
asm	52.0	66.5	19.6	27.1	ces	86.2	79.7	5.7	10.0	fra	89.5	86.4	6.3	8.0
hin	63.2	59.0	15.1	25.4	jav	53.8	68.6	10.8	23.5	kin	34.8	55.0	17.7	27.0
mal	54.0	62.0	15.3	26.4	npi	39.5	50.3	25.3	32.5	por	87.0	80.4	8.2	10.2
sna	21.5	62.7	22.8	22.1	swh	41.5	61.6	20.5	28.1	tur	78.2	74.0	9.8	15.2
yor	22.5	53.9	18.5	22.8	als	61.0	70.9	15.7	23.3	azj	63.8	65.8	15.1	23.8
ckb	5.0	47.7	38.9	21.6	fuv	29.2	60.4	21.5	26.1	hrv	80.5	77.8	8.1	13.6
jpn	76.2	87.5	7.5	11.7	kir	43.8	72.7	5.4	21.1	mar	59.5	65.0	12.7	24.4
nso	24.2	71.6	19.2	20.3	snd	26.0	63.9	10.6	19.3	tam	50.8	69.7	13.6	23.9
ukr	82.0	73.0	5.6	13.0	zho	86.5	86.6	2.6	8.5	amh	22.5	68.0	6.4	17.3
bam	28.8	67.5	20.7	23.6	dan	85.8	77.5	6.8	11.0	gaz	29.5	54.5	23.5	27.4
hun	72.2	74.9	15.7	19.6	kac	29.8	52.3	14.5	24.4	kor	82.8	76.9	4.3	12.0
mkd	76.8	75.3	6.2	15.7	nya	25.0	64.9	26.1	25.3	ron	81.8	77.5	7.8	13.1
som	29.8	59.0	25.1	27.7	tel	42.2	66.2	29.5	31.1	urd	63.8	67.8	6.5	21.1
zho	86.8	79.6	4.6	8.8	apc	70.2	69.1	6.9	19.4	ben	65.5	70.7	19.6	23.9
deu	90.2	80.2	4.8	7.6	grn	35.2	63.1	21.8	26.9	hye	23.0	63.1	8.8	19.0
kan	46.2	61.9	25.9	31.4	lao	5.5	62.6	28.6	15.3	mlt	44.2	67.2	25.3	29.1
ory	50.8	66.1	21.5	27.9	rus	86.8	79.0	5.6	10.0	sot	31.2	53.7	20.7	28.0
tgk	40.0	64.2	16.6	26.0	urd	47.5	64.1	21.9	28.7	zsm	80.2	76.4	4.2	12.8
arb	85.2	76.1	4.8	10.8	ben	33.0	57.7	27.9	30.6	ell	74.5	74.4	11.8	17.3
guj	55.2	67.4	12.7	24.1	ibo	18.8	54.1	29.5	26.1	kat	15.0	63.1	22.9	19.6
lin	28.8	57.3	32.7	32.5	mri	12.5	87.2	25.1	14.8	pan	50.0	65.7	18.8	26.8
shn	1.8	39.6	27.4	10.0	spa	88.5	85.2	6.2	8.4	tgl	68.5	74.0	9.5	19.4
uzn	59.8	70.2	11.8	22.3	zul	27.0	55.4	31.6	31.1	arb	31.5	68.0	16.8	22.6
bod	25.0	57.0	20.0	25.2	sun	49.8	64.2	17.0	26.9	hat	43.5	65.5	29.1	31.3
ilo	34.5	62.4	24.1	28.0	kaz	48.8	67.3	13.1	25.0	lit	68.5	71.3	14.3	20.8
mya	8.0	68.6	19.2	10.6	pbt	18.8	50.1	26.5	24.1	sin	30.5	61.6	19.2	24.6
srp	82.8	76.0	5.5	12.3	tha	48.0	72.9	3.8	21.0	vie	84.2	84.8	4.8	9.8
ars	71.8	72.6	3.1	17.6	bul	78.5	81.3	4.2	12.8	est	65.5	68.7	16.2	22.9
hau	26.5	54.9	30.1	30.4	ind	80.2	80.4	7.3	13.1	kea	47.2	63.1	30.1	33.2
lug	27.8	58.1	24.6	26.8	nld	84.5	83.2	9.6	11.2	pes	69.0	72.2	4.1	18.4
sin	25.2	69.1	27.2	24.2	ssw	25.2	65.6	23.8	23.8	tir	18.8	64.7	5.3	15.3
war	53.2	71.0	14.5	23.9	ary	63.0	66.1	8.3	22.1	cat	86.0	80.4	7.0	10.6
eus	46.2	64.8	18.0	26.8	heb	78.0	76.8	6.4	14.6	isl	61.0	68.3	17.6	24.9
khk	33.8	66.4	14.9	23.8	luo	30.8	57.1	21.9	27.1	nob	80.2	79.8	7.2	12.9
plt	35.5	64.4	8.5	22.5	slk	81.8	82.3	9.2	12.7	**eng**	**91.8**	**83.9**	**4.2**	**6.7**
tsn	28.8	62.0	23.6	26.3	wol	31.0	51.9	23.1	29.0	**Avg.**	**52.7**	**68.6**	**15.2**	**20.4**

Table 10: Per-language performance on the belebele test set for the **Qwen 2.5** model, reporting AUROC, ECE, and Brier score. Each row is color-coded, same as Table 8. English line and the Average line is **bolded**.

Set 1					Set 2					Set 3				
Lang	**Acc**	**AUR.**	**ECE**	**Brier**	**Lang**	**Acc**	**AUR.**	**ECE**	**Brier**	**Lang**	**Acc**	**AUR.**	**ECE**	**Brier**
acm	36.0	60.5	17.8	22.8	arz	38.5	65.0	11.6	22.6	ceb	36.0	60.4	19.9	22.9
fin	41.5	70.9	8.3	21.5	hin	41.8	60.8	11.8	23.7	ita	70.5	73.2	15.3	20.3
khm	20.2	53.7	29.7	18.9	lvs	40.2	68.6	16.4	22.2	npi	34.5	59.6	13.7	22.8
pol	58.8	71.5	9.8	21.8	slv	46.8	67.3	4.5	22.8	swe	58.8	76.7	12.2	20.4
tso	27.5	52.8	29.1	20.9	xho	26.2	51.8	31.1	21.1	afr	53.2	65.8	8.1	23.4
asm	26.8	59.6	20.7	19.6	ces	66.2	67.1	10.7	21.7	fra	69.5	75.0	15.1	19.8
hin	31.2	60.1	17.8	22.7	jav	39.2	61.0	13.4	22.9	kin	27.5	54.3	26.5	20.9
mal	28.2	60.4	23.5	21.0	npi	28.2	47.9	37.3	23.3	por	65.5	75.2	13.3	20.2
sna	24.0	50.2	35.5	20.2	swh	31.8	61.5	15.7	22.7	tur	47.2	63.1	11.7	23.9
yor	25.0	51.7	29.7	19.8	als	43.8	62.6	10.3	23.6	azj	33.0	60.5	20.1	22.0
ckb	28.8	51.9	27.4	21.6	fuv	10.5	48.4	39.0	13.7	hrv	51.0	67.9	4.1	22.4
jpn	54.2	66.3	12.0	23.8	kir	24.2	54.6	36.7	21.2	mar	37.0	57.1	11.9	23.5
nso	26.5	56.0	24.8	20.2	snd	13.5	44.3	38.7	18.0	tam	32.5	59.1	30.7	23.5
ukr	62.0	71.8	19.2	21.9	zho	25.8	53.0	26.1	23.9	amh	25.5	53.4	34.9	19.8
bam	28.2	54.7	28.1	20.6	dan	53.0	74.8	7.9	20.8	gaz	25.8	49.2	28.6	20.4
hun	54.8	70.6	6.7	21.9	kac	25.2	49.0	36.7	20.5	kor	55.0	65.4	11.0	24.0
mkd	50.0	68.4	9.8	22.6	nya	27.8	47.5	33.8	22.0	ron	35.2	57.9	25.6	26.0
som	25.2	53.4	27.3	20.1	tel	27.8	53.8	29.4	22.2	urd	17.2	47.7	42.8	23.4
zho	54.2	73.3	23.8	26.5	apc	37.0	64.8	11.6	22.1	ben	31.2	58.2	23.5	21.7
deu	65.8	74.5	11.9	20.0	grn	31.0	58.7	18.9	21.8	hye	17.0	48.7	31.0	16.8
kan	27.8	57.9	23.1	23.5	lao	27.0	44.3	40.1	21.3	mlt	33.0	61.4	15.0	21.4
ory	30.2	52.5	22.0	21.5	rus	59.2	72.9	19.9	23.4	sot	23.2	52.5	34.9	19.9
tgk	26.5	52.2	38.7	20.9	urd	26.5	56.6	34.0	20.6	zsm	56.5	71.0	17.2	23.9
arb	47.5	67.2	15.2	23.3	ben	28.0	50.0	36.6	21.8	ell	54.5	75.0	9.0	20.6
guj	28.5	53.0	31.6	22.7	ibo	26.0	52.3	31.8	21.0	kat	27.5	59.1	23.8	21.6
lin	27.5	54.0	29.1	20.9	mri	28.8	54.1	35.0	21.6	pan	29.5	54.1	31.3	22.1
spa	68.2	67.4	22.6	23.3	tgl	41.2	64.8	14.9	22.7	tsn	26.8	55.7	26.8	20.6
uzn	35.0	59.7	24.4	22.7	zul	27.2	51.5	19.6	20.9	plt	31.8	58.2	20.5	21.7
bod	27.2	45.7	33.7	22.1	hat	30.8	52.8	19.5	22.5	wol	27.2	52.2	28.0	21.4
ilo	30.2	57.3	22.4	21.4	kaz	29.5	50.2	35.4	22.6	lit	42.8	65.7	18.5	23.1
pbt	22.8	57.5	24.8	18.7	sin	24.5	51.0	46.5	20.3	srp	54.5	70.4	16.7	23.2
tha	48.5	66.7	11.6	23.5	vie	59.5	73.6	11.4	21.2	ars	38.0	62.4	17.3	23.1
bul	49.5	71.8	14.5	22.3	est	37.0	60.7	14.0	23.4	hau	25.0	53.5	34.0	19.9
ind	60.8	73.8	17.7	21.7	kea	37.2	59.3	15.2	23.6	lug	28.2	48.7	24.4	21.6
nld	62.5	75.5	15.7	20.7	pes	57.2	65.7	14.7	23.7	sin	32.2	54.6	28.4	22.4
ssw	25.2	54.6	25.5	20.0	tir	23.8	49.8	34.9	19.0	war	36.0	58.3	20.6	22.8
ary	30.0	61.2	20.9	21.7	cat	65.0	71.1	11.9	21.6	eus	37.8	64.6	10.7	22.3
heb	39.5	68.8	16.9	21.7	isl	34.8	56.0	17.3	23.6	khk	27.0	56.6	26.3	20.4
luo	26.2	57.1	23.8	19.6	nob	53.2	70.0	13.3	22.3	**eng**	**73.5**	**79.5**	**10.5**	**16.3**
slk	56.8	72.3	16.6	21.5	sun	36.0	57.3	12.7	22.8	**Avg.**	**37.3**	**59.7**	**22.2**	**21.7**

Table 11: Per-language performance on the belebele test set for the **Deepseek** model, reporting AUROC, ECE, and Brier score. Each row is color-coded, same as Table 8. Language entries with lower than 5% accuracy is excluded. English line and the Average line is **bolded**.

Set 1					Set 2					Set 3				
Lang	**Acc**	**AUR.**	**ECE**	**Brier**	**Lang**	**Acc**	**AUR.**	**ECE**	**Brier**	**Lang**	**Acc**	**AUR.**	**ECE**	**Brier**
acm	21.2	77.2	10.3	15.3	arz	17.5	74.5	14.0	14.1	ceb	39.5	64.9	22.2	27.9
fin	53.0	69.5	17.4	25.3	hin	5.0	68.6	18.5	8.6	ita	73.2	75.3	11.4	17.5
pol	61.2	71.0	9.9	21.4	slv	66.0	68.4	9.7	21.1	swe	71.8	72.7	7.1	17.8
tso	26.5	54.5	20.2	24.7	xho	26.5	55.1	22.5	25.9	afr	60.2	69.5	14.3	23.3
ces	65.0	69.5	6.4	20.5	fra	74.8	71.6	5.1	16.6	lvs	38.5	61.9	13.2	25.6
hin	38.0	63.0	20.6	27.0	jav	35.2	58.2	21.1	28.0	kin	26.5	53.0	21.8	25.4
npi	29.0	47.2	18.8	26.6	por	75.8	73.5	7.8	16.3	sun	30.5	53.0	21.1	28.0
sna	29.5	54.0	20.4	26.4	swh	29.0	60.5	29.4	29.6	tur	27.0	62.1	22.8	25.8
yor	22.0	51.6	15.7	21.4	als	35.2	64.0	16.9	25.1	azj	19.0	54.4	22.6	24.2
jpn	21.2	71.5	13.9	17.2	kir	30.0	57.9	7.2	22.9	mar	5.5	56.6	17.3	8.9
nso	26.0	49.4	18.7	24.8	tam	8.8	48.5	21.5	14.6	ukr	69.8	66.8	5.6	19.8
zho	54.0	81.2	4.2	17.6	ssw	25.5	54.9	20.2	23.8	fuv	20.2	42.9	20.0	23.2
bam	24.0	57.5	21.5	25.3	dan	72.2	68.9	7.8	18.5	gaz	23.8	57.0	20.2	22.8
hun	61.2	71.1	11.3	21.4	kac	27.2	48.0	16.9	23.7	kor	25.8	60.3	9.5	20.1
mkd	54.2	67.3	7.3	23.2	nya	28.5	55.2	20.0	25.6	ron	68.2	72.5	6.7	18.5
som	26.0	54.7	20.6	25.0	zho	49.5	81.0	5.8	17.9	apc	18.5	69.3	13.1	15.4
deu	70.2	70.8	8.1	18.9	grn	30.8	53.0	19.9	27.6	mlt	29.2	58.1	17.1	24.8
rus	72.0	70.2	5.6	18.1	sot	25.5	52.4	17.1	23.0	tgk	22.0	48.7	9.9	20.4
urd	29.0	57.7	20.4	25.3	zsm	58.8	71.1	12.7	22.8	arb	27.5	78.2	8.0	16.2
ben	30.0	55.0	21.3	26.4	hrv	68.2	72.2	9.8	19.8	ell	6.8	46.5	32.2	20.2
ibo	18.8	42.1	28.2	27.9	lin	27.2	49.5	19.3	25.8	mri	26.8	45.9	21.4	26.2
spa	72.8	70.6	6.3	18.1	tgl	49.0	71.2	17.7	24.9	uzn	30.2	64.8	20.9	24.8
zul	22.2	51.6	23.5	24.4	arb	17.2	46.8	14.5	19.4	hat	33.5	58.4	23.9	28.7
kaz	26.5	51.4	10.1	22.0	lit	41.0	64.2	13.8	25.2	sin	26.2	51.1	13.9	23.1
srp	68.5	68.3	7.5	20.2	tha	11.8	54.6	14.3	14.0	vie	27.5	50.6	39.2	38.0
ars	19.2	82.4	12.3	13.4	bul	67.8	71.5	5.5	19.2	est	43.8	59.5	16.0	27.6
hau	21.5	46.5	22.0	25.9	ind	62.8	72.5	12.3	21.7	kea	35.8	59.0	23.6	29.5
lug	26.0	57.2	23.7	25.5	nld	68.5	74.0	13.0	19.5	ilo	28.5	56.4	24.4	27.5
war	35.5	61.5	27.5	30.7	ary	16.2	74.8	12.6	13.5	cat	71.2	75.8	10.1	17.6
eus	30.0	53.8	17.6	25.1	heb	10.0	62.1	26.7	17.0	isl	23.2	59.4	28.8	27.5
khk	23.5	51.3	8.9	21.2	luo	25.8	48.4	20.1	25.0	**eng**	**80.8**	**83.3**	**10.6**	**13.3**
tsn	27.2	47.3	20.1	26.4	wol	22.8	47.7	20.4	24.2	**Avg.**	**32.2**	**56.6**	**19.8**	**22.1**

Table 12: Per-language performance on the belebele test set for the **Mistral** model, reporting AUROC, ECE, and Brier score. Each row is color-coded, same as Table 8. Language entries with lower than 5% accuracy is excluded. English line and the Average line is **bolded**.

Set 1					Set 2					Set 3				
Lang	**Acc**	**AUR.**	**ECE**	**Brier**	**Lang**	**Acc**	**AUR.**	**ECE**	**Brier**	**Lang**	**Acc**	**AUR.**	**ECE**	**Brier**
acm	73.0	81.3	6.1	15.2	arz	82.5	85.5	5.1	10.8	ceb	69.2	79.3	6.9	16.5
fin	89.5	85.4	4.1	7.4	hin	79.0	81.2	5.7	13.0	ita	89.5	92.2	6.0	6.4
lvs	84.8	87.8	8.6	9.5	npi	73.0	80.8	9.1	15.2	pol	90.5	88.9	7.2	6.6
slv	90.5	91.3	7.0	6.2	swe	89.8	86.8	6.6	6.9	tso	37.2	62.0	6.0	22.4
xho	38.0	65.2	8.5	22.1	afr	91.2	82.9	6.7	6.7	ces	90.0	90.0	9.3	7.0
fra	93.5	88.9	11.2	5.6	hin	67.2	73.7	3.8	18.8	jav	78.8	82.0	3.3	12.4
kin	33.2	63.4	6.3	21.3	por	93.2	93.0	7.9	5.0	sna	36.8	62.6	6.3	22.6
swh	79.0	78.6	4.2	13.2	tur	87.0	86.0	5.6	8.7	yor	37.0	56.6	8.9	23.8
als	83.2	88.0	5.3	9.8	azj	72.8	78.9	3.4	15.8	fuv	27.0	54.6	9.6	21.3
hrv	89.5	89.0	5.1	6.9	jpn	85.5	84.9	12.2	10.0	kir	69.8	78.0	7.3	17.4
nso	35.8	60.9	5.8	22.6	tam	75.0	78.2	4.2	14.9	ukr	91.5	90.0	5.8	6.2
zho	88.2	92.7	11.3	7.5	bam	35.5	58.6	5.1	22.5	dan	92.0	87.5	6.4	5.7
gaz	30.8	52.5	7.0	22.0	hun	90.0	85.5	3.7	6.5	kac	32.5	53.7	8.0	22.7
kor	88.5	83.2	7.7	8.2	mkd	86.0	88.6	6.9	8.9	nya	35.0	64.0	4.8	21.9
ron	90.0	89.1	5.5	6.7	som	28.2	54.0	15.7	24.0	zho	88.5	92.4	11.9	7.0
apc	77.2	83.4	7.3	13.6	deu	93.8	86.0	6.8	4.9	grn	35.2	66.0	14.7	22.8
mlt	63.5	73.2	7.0	19.9	ory	74.8	79.0	7.5	15.7	rus	91.8	92.0	4.7	5.3
sot	32.5	59.6	5.7	21.7	tgk	55.5	72.0	5.8	21.2	urd	46.2	65.8	2.6	23.0
zsm	88.8	85.1	4.4	7.5	arb	90.8	85.2	6.1	6.7	ben	34.0	59.8	12.8	23.0
ell	88.5	90.4	8.9	7.8	wol	32.7	52.8	9.5	24.0	ibo	28.2	57.5	11.0	21.4
lin	32.2	61.3	13.9	22.9	mri	37.0	60.0	8.3	23.3	pan	79.0	87.2	7.8	11.8
spa	91.3	90.5	5.8	6.1	tgl	83.3	83.4	5.1	11.1	zul	35.3	58.6	6.3	22.4
hat	58.7	78.3	9.5	19.1	ilo	43.3	73.9	7.7	20.7	kaz	64.7	82.3	9.4	16.7
lit	86.7	89.5	12.9	9.0	arb	26.0	61.4	7.9	19.0	pbt	59.3	66.3	12.5	22.4
sin	27.3	59.0	6.8	20.0	srp	90.7	95.1	8.0	5.5	tha	47.3	65.2	18.6	26.8
vie	92.0	93.1	8.6	5.4	ars	78.7	84.7	8.0	11.3	bul	89.3	89.0	9.8	6.9
est	79.3	82.4	4.2	12.8	hau	38.7	56.1	10.8	23.9	ind	88.7	93.6	7.0	6.9
kea	56.7	72.4	11.5	21.8	lug	24.7	55.1	16.1	22.1	nld	90.0	86.9	5.4	7.2
ssw	26.0	61.4	15.8	20.1	war	52.7	77.5	11.1	20.3	ary	64.0	80.4	10.4	17.3
cat	91.3	85.6	4.4	6.2	eus	70.0	75.9	6.8	17.3	heb	90.0	83.2	10.3	8.6
isl	83.3	78.6	3.3	11.1	khk	58.0	60.9	11.2	24.4	luo	30.7	52.1	12.8	23.5
nob	88.0	83.2	4.3	8.3	plt	57.3	81.3	11.2	17.8	**eng**	**94.0**	**89.0**	**6.9**	**3.6**
sun	50.7	72.8	11.6	21.2	tsn	30.7	57.9	10.7	22.4	**Avg.**	**65.4**	**75.5**	**9.1**	**15.3**

Table 13: Per-language performance on the belebele test set for the **Phi** model, reporting AUROC, ECE, and Brier score. Each row is color-coded, same as Table 8. Language entries with lower than 5% accuracy is excluded. English line and the Average line is **bolded**.

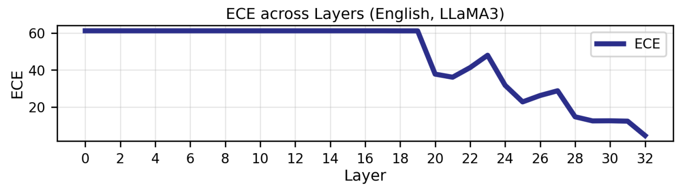


Figure 7: Layer-wise predicted confidence ECE for English in LLaMA3.

C Layer-Wise Calibration Analysis

C.1 English Calibration Improves as Layer Deepens

Figure 7 shows the layer-wise Expected Calibration Error (ECE) for English in LLaMA3, illustrating how calibration improves progressively in deeper layers.

C.2 Multilingual Calibration is Best at Late-Intermediate Layers

We visualize calibration performance across layers by plotting metrics against entropy on the MMMLU dataset in LLaMA3 (Figure 8), Cohere (Figure 9), Mistral (Figure 10), Phi (Figure 11), Deepseek (Figure 12), Qwen 2.5 (Figure 13).

C.3 Reliability Diagrams

Figures 14 and 15 present reliability diagrams for LLaMA3 and Aya, respectively, illustrating calibration behaviour across languages and comparing intermediate versus final layers.

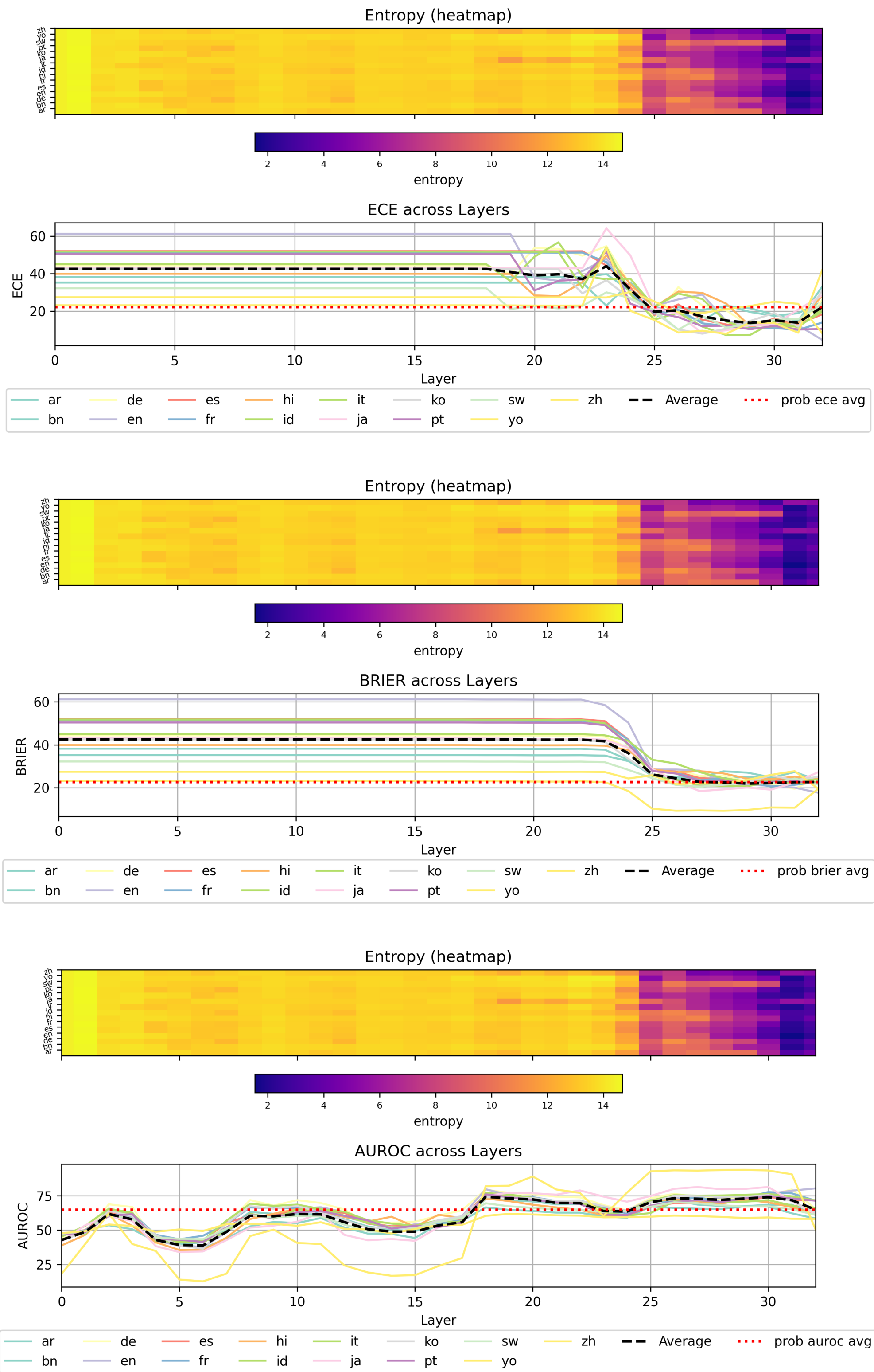


Figure 8: Calibration metrics (ECE, Brier score, AUROC) vs. entropy across layers on the MMMLU subset for LLaMA3.

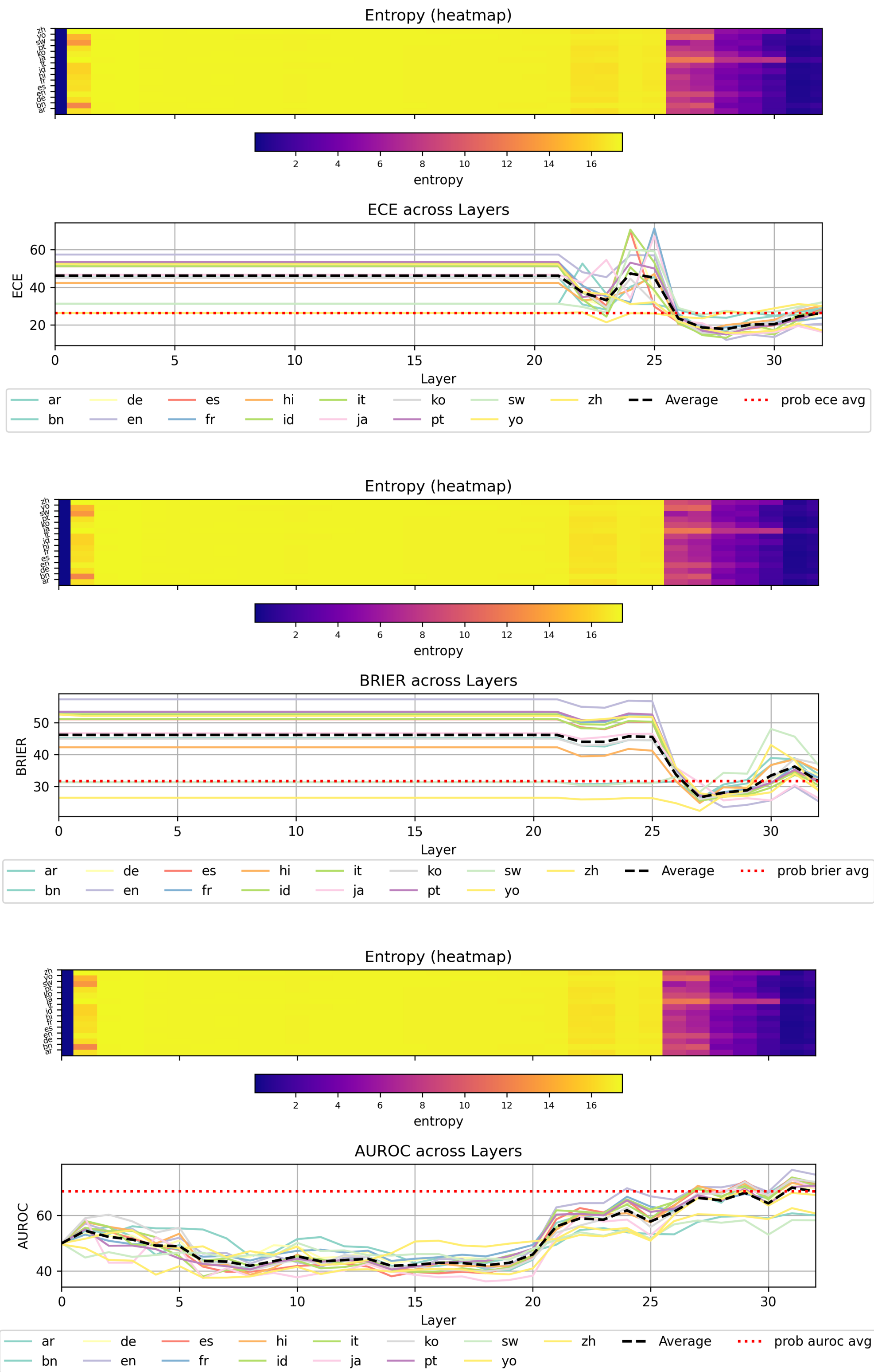


Figure 9: Calibration metrics (ECE, Brier score, AUROC) vs. entropy across layers on the MMMLU dataset for Aya.

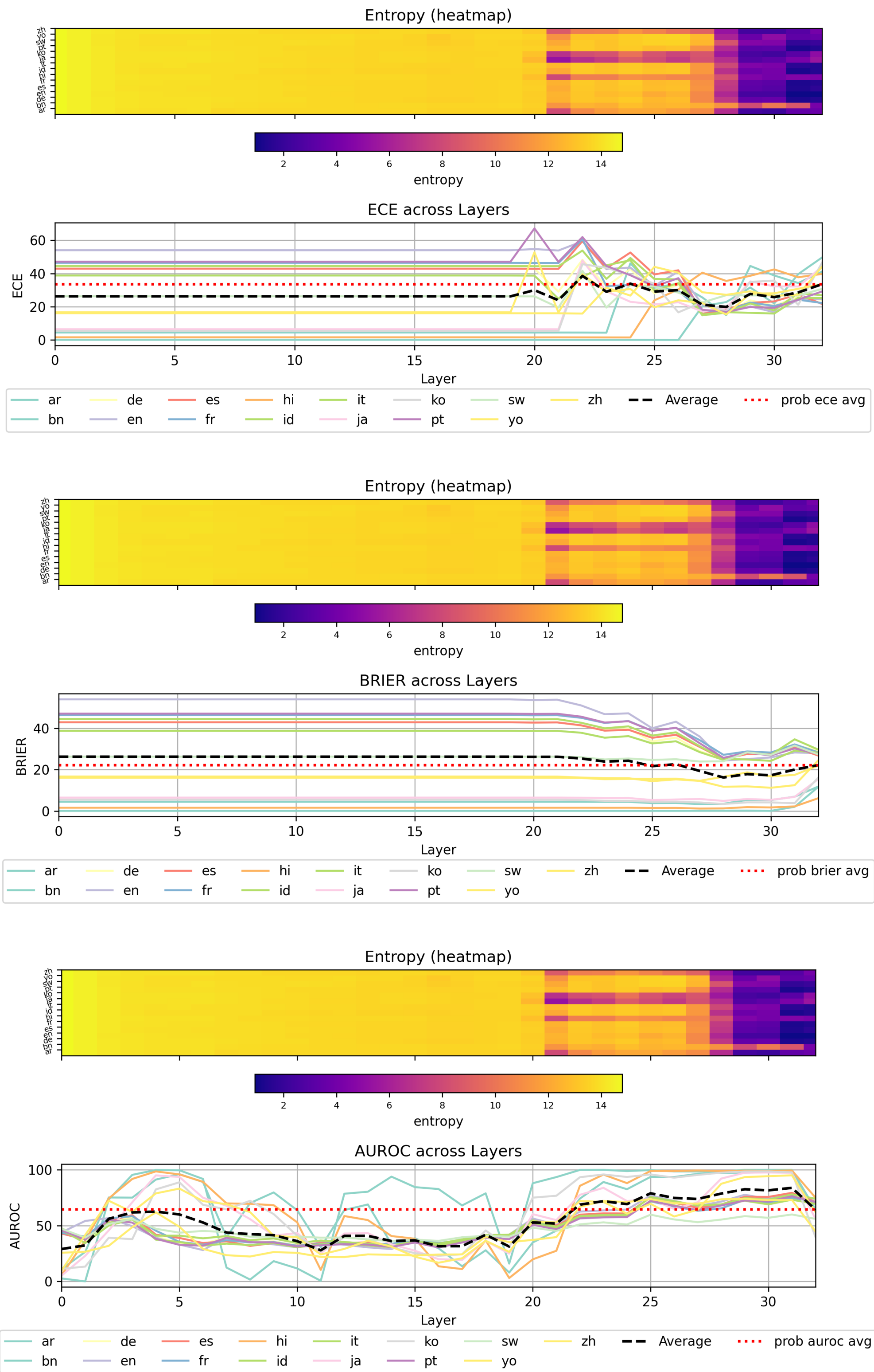


Figure 10: Calibration metrics (ECE, Brier score, AUROC) vs. entropy across layers on the MMMLU dataset for Mistral.

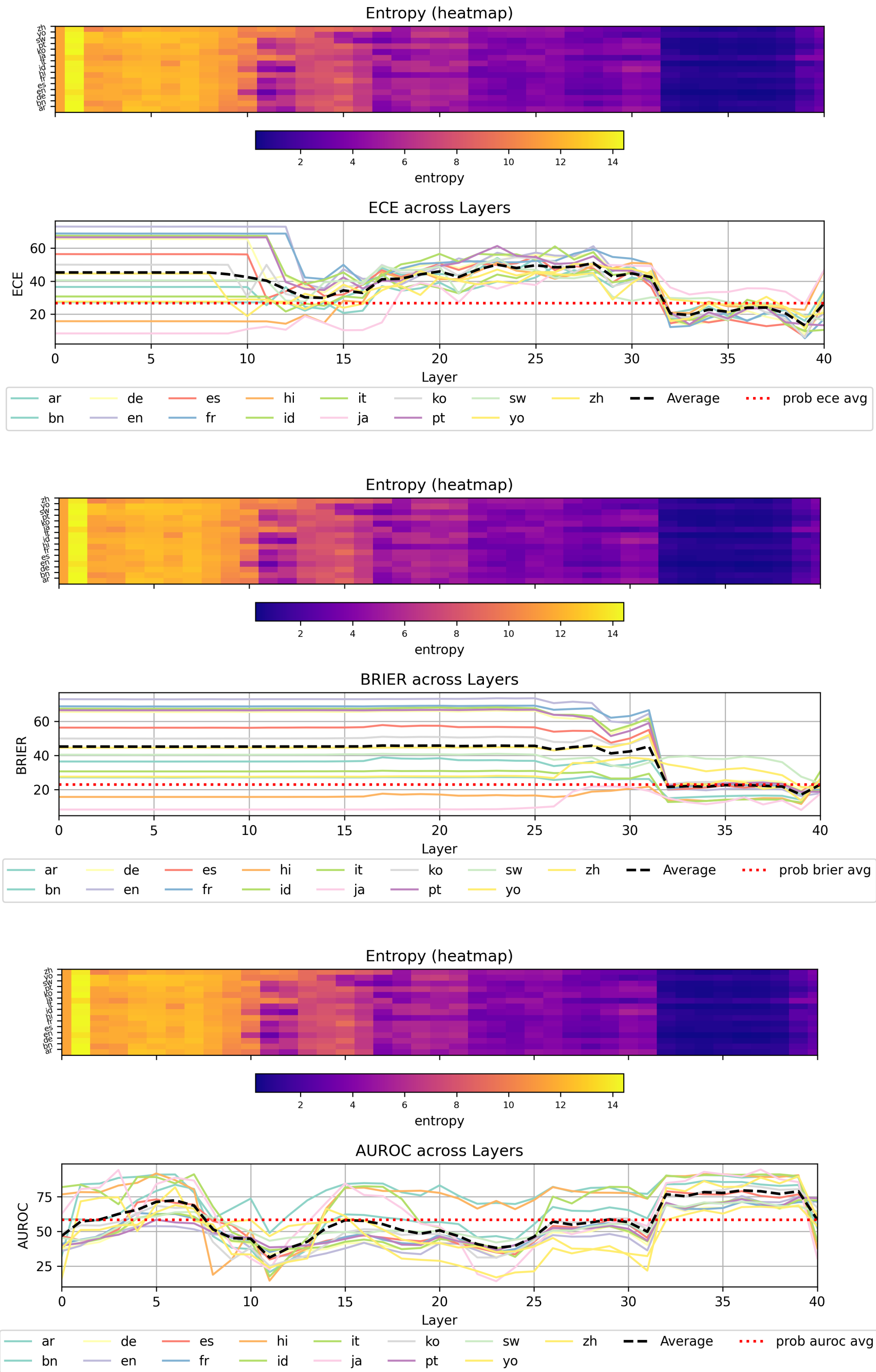


Figure 11: Calibration metrics (ECE, Brier score, AUROC) vs. entropy across layers on the MMMLU dataset for Phi.

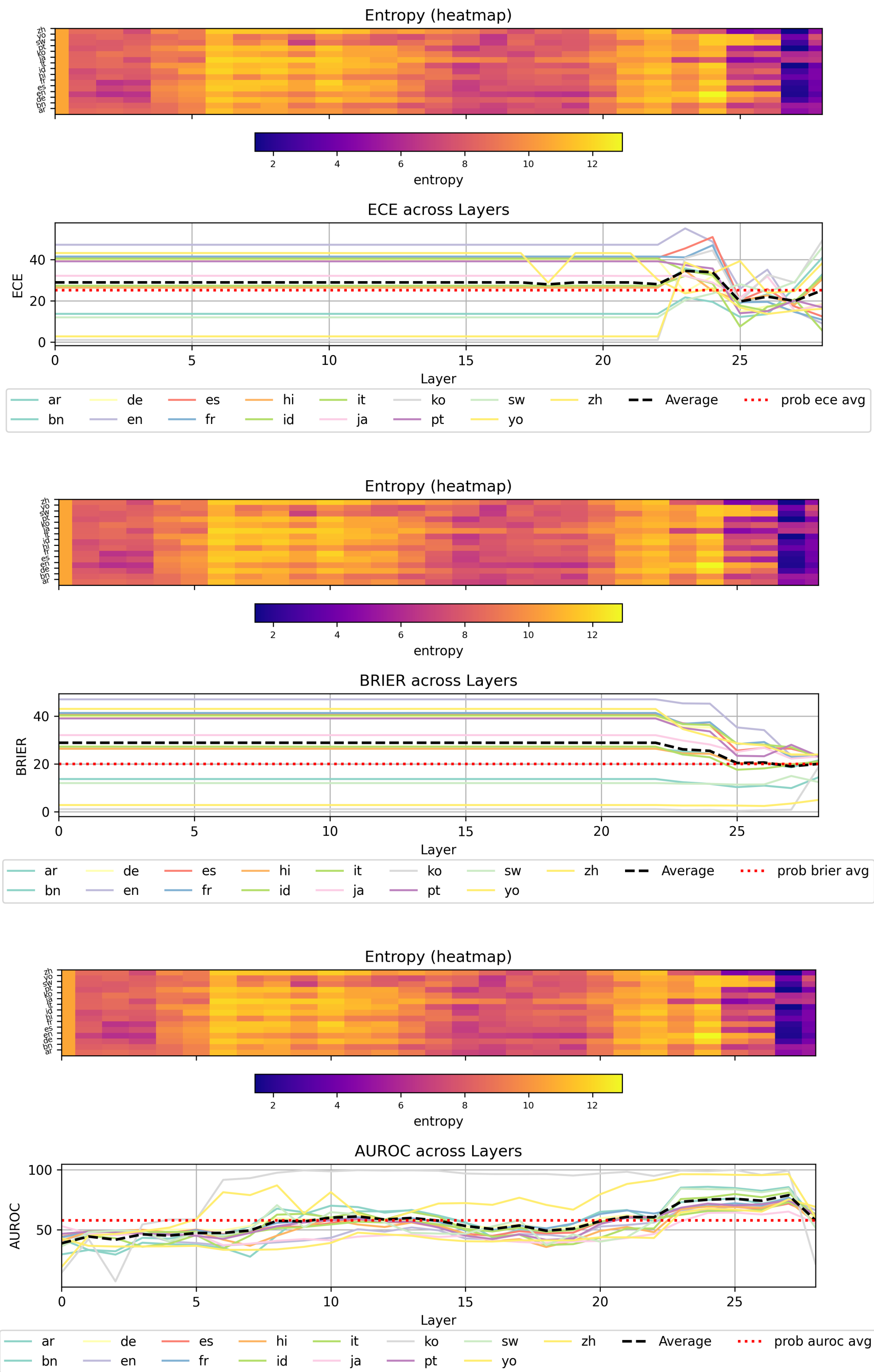


Figure 12: Calibration metrics (ECE, Brier score, AUROC) vs. entropy across layers on the MMMLU dataset for Deepseek.

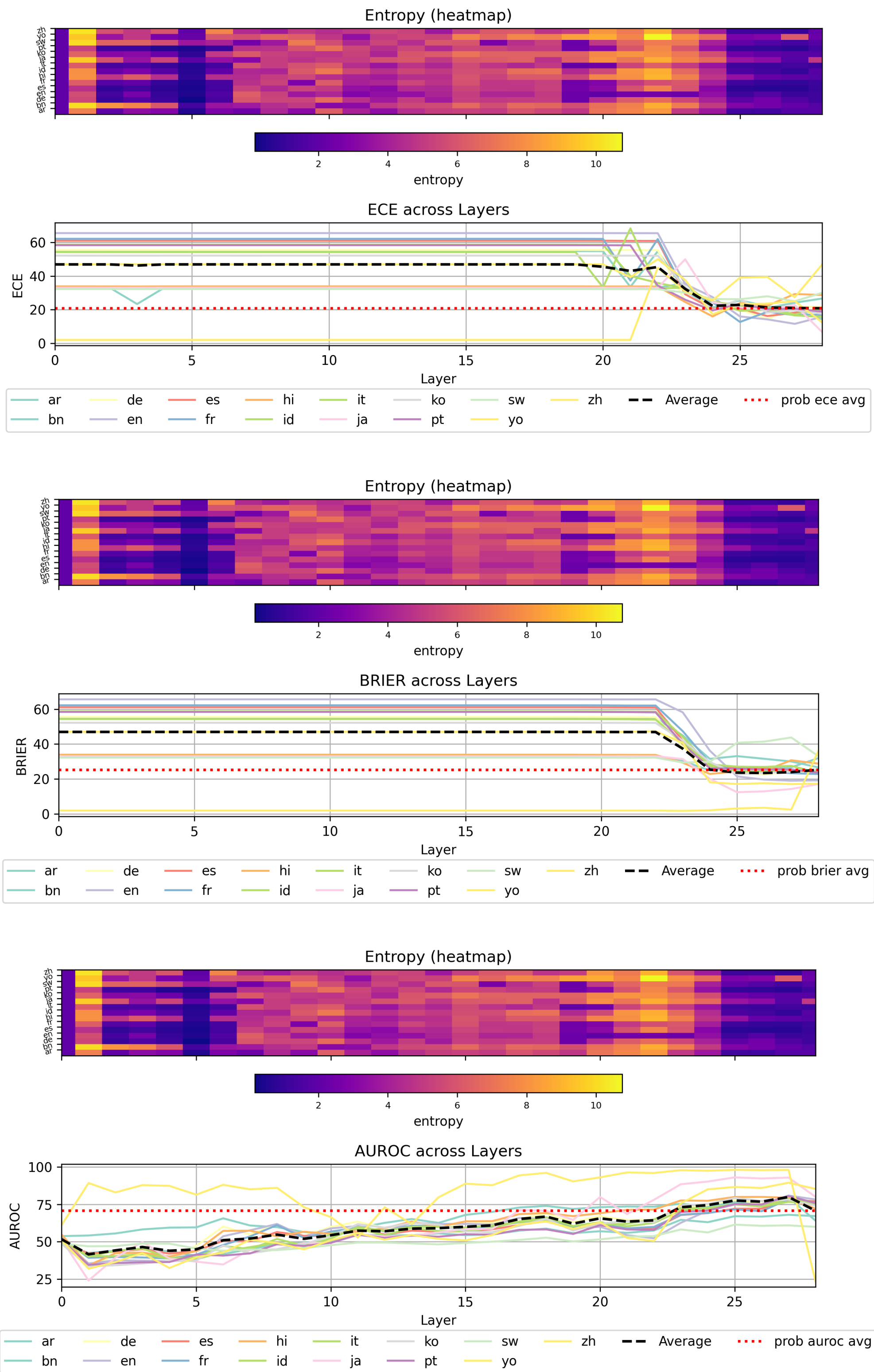


Figure 13: Calibration metrics (ECE, Brier score, AUROC) vs. entropy across layers on the MMMLU dataset for Qwen 2.5.

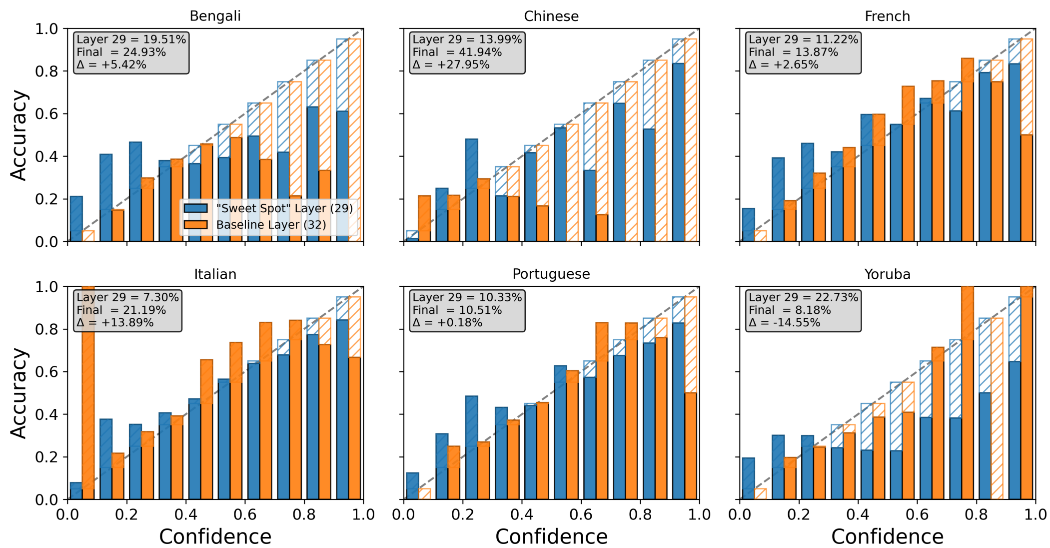


Figure 14: showing calibration curves for the remaining languages in LLaMA3: Bengali, Chinese, French, Italian, Portuguese, and Yoruba. Each plot compares the "sweet spot" intermediate layer (Layer 29, blue) against the final layer (Layer 32, orange). Bars represent accuracy across confidence bins, with diagonal dashed lines indicating perfect calibration. Reported values denote ECE for Layer 29 and the final layer, along with the relative improvement (Δ).

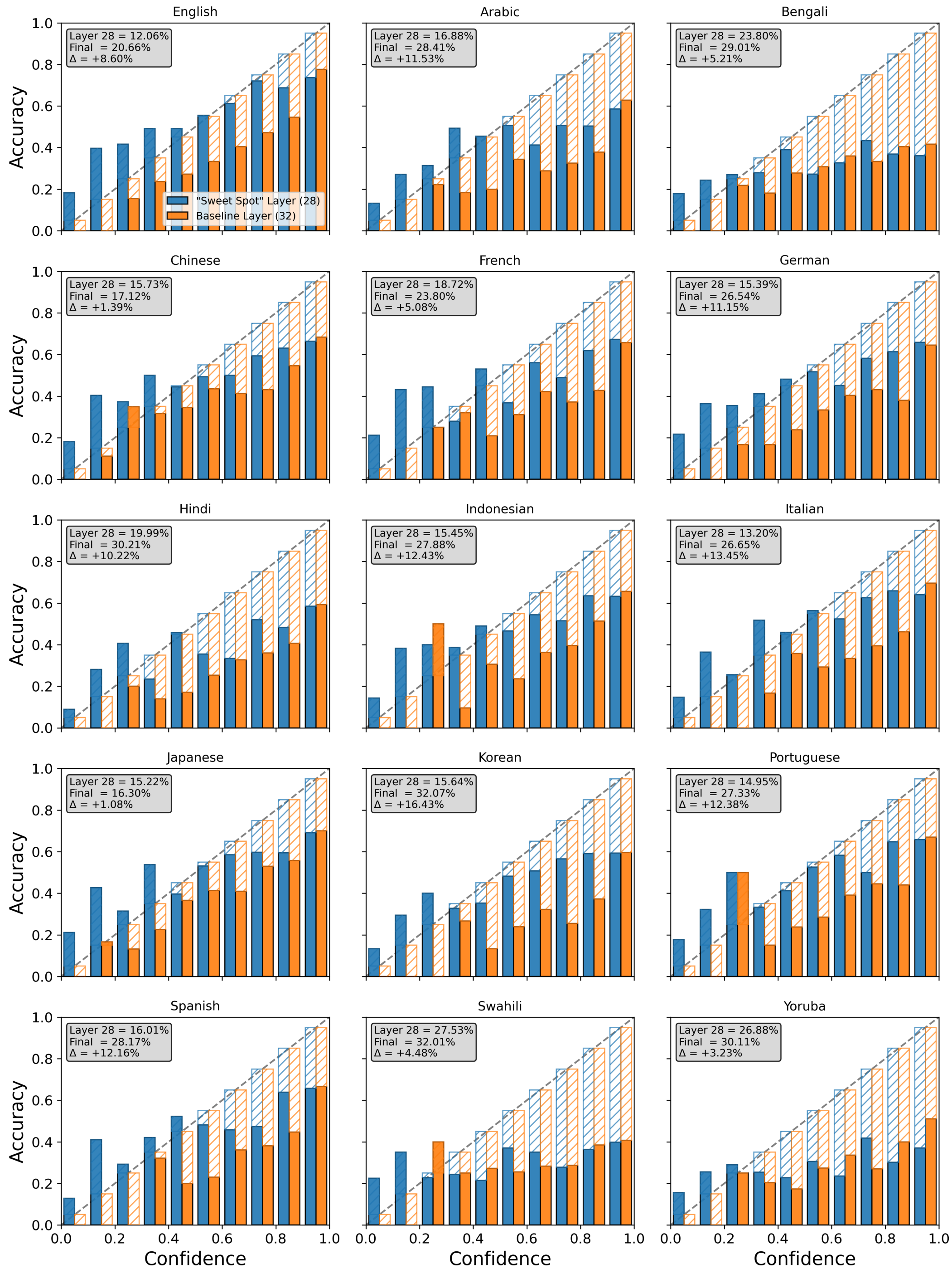


Figure 15: Reliability diagrams for Aya across all evaluated languages. Each plot compares the "sweet spot" intermediate layer with the final layer. Blue bars represent accuracy across confidence bins for the intermediate layer, while orange bars represent the final layer. The diagonal dashed line indicates perfect calibration. Reported values denote the ECE for Layer 28 and final layer, along with the relative improvement (Δ), highlighting how calibration changes across layers in different languages.

D Post-hoc Calibrators

We include two widely used post-hoc calibration methods as baselines: **Temperature Scaling** [Guo et al., 2017] and **Isotonic Regression** [Zadrozny and Elkan, 2002]. Both are trained on a held-out validation set (15k examples from MMMLU and 12k examples from Belebele, non-overlapping with the evaluation sets). The fitted calibrators are then applied to test-set predictions, and metrics (ECE, AUROC, Brier score, Accuracy) are computed using the calibrated probabilities.

Temperature Scaling Temperature scaling applies a single scalar parameter $T > 0$ to rescale logits before computing probabilities. The parameter is optimized by minimizing the **negative log-likelihood (NLL)** on the validation set. In practice, we perform a coarse-to-fine grid search: first over a wide range ($T \in [0.05, 5.0]$ with 60 candidates), then locally refining around the best value with a denser grid. This procedure provides stable estimates across languages and avoids degenerate minima. The resulting optimal temperature is then used to rescale logits of all models prior to evaluation.

Isotonic Regression Isotonic regression learns a non-parametric, monotone mapping from predicted probabilities to calibrated probabilities in $[0, 1]$. We use the `scikit-learn` implementation with out-of-bounds clipping and monotonicity constraints. The model is fitted on the validation set and then applied to test-set predictions.