Aligning Cultural Behaviors in Arabic Language Models via Preferences

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ARABPREF

Abstract

Arabic LLMs have improved rapidly, but aligning them with country-specific cultural behavioral preferences remains underexplored. Previous work has focused primarily on instruction-tuning for factual knowledge, overlooking nuanced cultural behaviors. We propose ARABPREF, which to our knowledge is the first large-scale pan-Arab preference data set for the alignment of cultural behavior conditioned on the country. Our contribution includes two resources in English and Modern Standard Arabic: a culturally grounded preference dataset for training and evaluation, and a multiple-choice benchmark designed to assess culturally aligned behavior across nations. All test data are validated by native speakers to ensure authenticity. To optimize cultural alignment, we experiment with post-training methods across multilingual and Arabic-centric language models, evaluating performance on both generation tasks and our cultural multiple-choice benchmark. By releasing both a training dataset and an evaluation benchmark, we provide a foundation for systematically studying and improving culturally aligned behavior in language models.

1 Introduction

People from different cultural backgrounds communicate and interact according to different social norms. As large language models (LLMs) become part of communication, supporting multiple languages is not enough; models must also respond in ways that fit the cultural contexts of their users. Culture shapes communication norms, meaning, and judgments of appropriateness. Despite progress in multilingual modeling (Ahuja et al., 2023; Yong et al., 2023), LLMs still struggle to recognize cultural cues and adapt to contexts (Hershcovich et al., 2022). As a result, factually correct outputs may be inappropriate or insensitive, which can reduce trust and reinforce harmful stereotypes (Liu, 2023).

Recent work has documented several aspects of this problem. LLMs often reflect Western value profiles, including in evaluations designed to capture cross-cultural differences (Cao et al., 2023; Arora et al., 2023; Johnson et al., 2022; Abdulhai et al., 2024; Naous et al., 2024). Studies of cultural commonsense and geographically diverse factual knowledge further show that models have difficulty handling local practices, including regional food traditions, socially grounded norms, and time expressions (Nguyen et al., 2023; Yin et al., 2022). Other analyses examine how model representations of cultural values compare with those found in human societies and everyday dialogue (Dokic et al., 2025; Liu et al., 2026; Khan et al., 2025; Al Kautsar et al., 2026). Together, these studies point to two recurring gaps: model value profiles often differ from those of the populations they are expected to represent, and model decisions in social and economic settings only partly agree with human preferences across regions. These gaps are particularly important in non-English and non-Western settings, where Western-centered defaults may be less appropriate.

We study country-conditioned behavioral appropriateness in culturally situated social scenarios. This framing treats culture as context-dependent rather than as a fixed identity or a universal set of values (Naous et al., 2024). Arabic provides a useful setting for this study. It is spoken by more than 400 million people across 22 countries that share broad cultural ties but differ substantially in norms, traditions, and everyday practices. Treating Arabic-speaking populations as a single homogeneous group can obscure country-specific behavioral expectations and make cultural alignment gains difficult to interpret. This motivates our focus on country-conditioned preferences and our evaluation of culturally appropriate behavior across both English and Arabic settings.

Proceedings of the 2026 Conference on Empirical Methods in Natural Language Processing, pages 7810–7838
October 24-29, 2026 ©2026 Association for Computational Linguistics

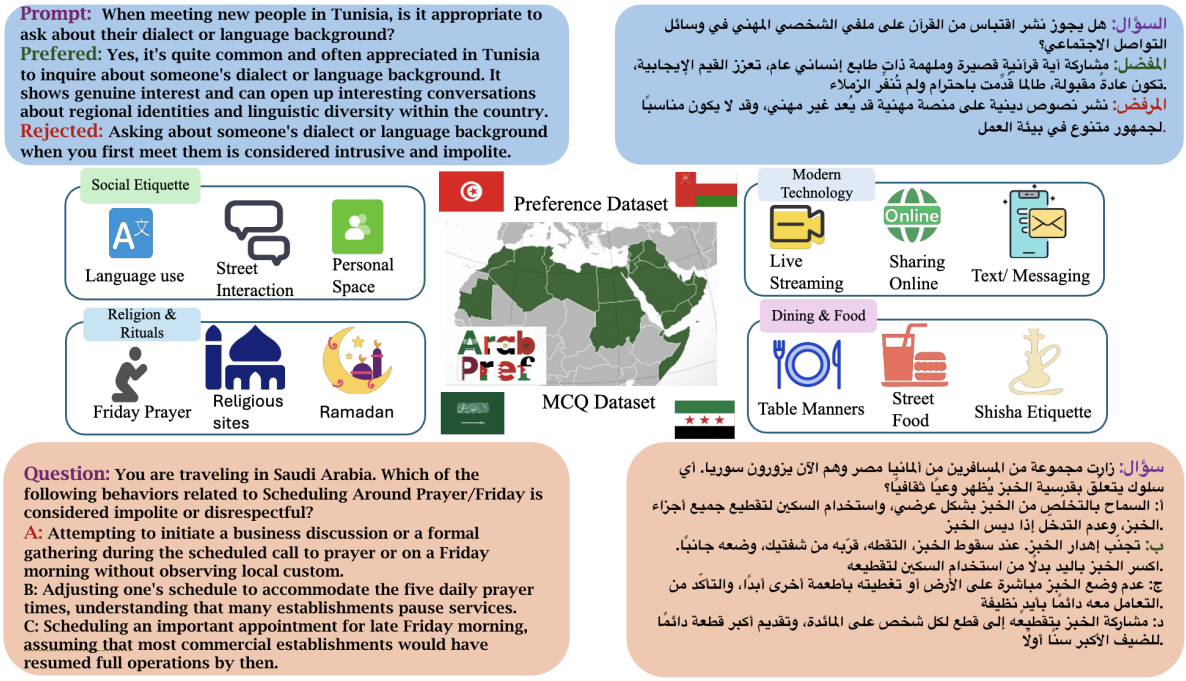

Figure 1: An Overview of our **ARABPREF** dataset, covering preference and MCQ data across 22 Arab League countries, spanning multiple categories and evaluation aspects, and available in English and Arabic. The upper part demonstrates two preference dataset samples in English and Arabic from Tunisia and Oman, respectively, while the bottom part demonstrates two MCQs from Saudi Arabia and Syria.

Our contributions are summarized as follows:

1. We introduce **ARABPREF**, the first large-scale behavioral preference dataset spanning all 22 Arab League countries. It covers 200 culturally grounded aspects across 16 categories, including social etiquette, religion, family and gender roles, food, work, and travel, and is released in both English and Modern Standard Arabic (MSA). ARABPREF consists of 31,060 training and 6,264 test preference pairs, culturally grounded triples for alignment and generation, and a native-speaker-validated multiple-choice benchmark with 1,984 questions for evaluation.

2. Using **ARABPREF**, we assess how multilingual and Arabic-centric LLMs represent Arab cultural behavior and whether preference alignment improves cultural robustness. Across open-source models, countries, languages, and cultural categories, we compare supervised fine-tuning (SFT), Direct Preference Optimization (DPO), and Kahneman-Tversky Optimization (KTO), finding that training on ARABPREF improves culturally aligned behavior and downstream cultural reasoning over existing datasets.

2 Related Work

Cultural grounding and evaluation in Arabic NLP. Recent work in Arabic NLP has highlighted the need to go beyond linguistic competence toward culturally grounded modeling. While large Arabic and multilingual language models perform well on standard benchmarks, they often fail to reflect culturally appropriate behavior in socially sensitive domains such as etiquette and religion. To address this gap, CIDAR (Alyafeai et al., 2024) and PALM (Alwajih et al., 2025) introduce culturally grounded Arabic instruction-following datasets curated by native speakers, and ArabCulture (Sadallah et al., 2025) proposes a multiple-choice benchmark for evaluating cultural commonsense reasoning. However, as summarized in Table 1, these resources primarily focus on instruction compliance or answer selection and do not explicitly model *normative behavioral preferences*.

Cultural alignment in LLMs. A body of work studies cultural alignment in large language models across regions and societies. Studies show that LLMs often default to Western—frequently American—value profiles when evaluated across cultures (Cao et al., 2023; Arora et al., 2023; Johnson et al., 2022; Abdulhai et al., 2024). Analyses grounded

Dataset	Arab-Specific	Topic Granularity	Prefs	Eval (MCQ)	Human Valid.	Langs	Scale
CARE	Partial	–	Yes	No	Yes	Multi (incl. Ar)	∼3.5K Q / 32K prefs
CIDAR	Yes	17 topics	No	No	Yes	Ar (MSA)	10K instr.
PALM	Yes	20 (coarse)	No	No	Yes	Ar (MSA + Dial.)	∼17.4K instr.
ARABCULTURE	Yes	12 domains	No	Yes	Yes	Ar (MSA)	∼3.5K MCQs
ARABPREF (Our)	**Yes**	**200 (fine)**	**Yes**	**Yes**	**Yes**	**Ar (MSA), En**	**31K train / 6K test / 2K MCQ**

Table 1: Comparison of cultural datasets for analyzing and aligning LLM behavior. Existing resources focus on instruction tuning (CIDAR, PALM), evaluation (ARABCULTURE), or limited preference annotation (CARE). ARABPREF uniquely combines pan-Arab coverage, fine-grained topics, and explicit behavioral preferences, enabling controlled preference-based alignment and assessment. Unlike CIDAR and PALM, ARABPREF supports preference optimization; unlike ARABCULTURE, it supports both training and evaluation; unlike CARE, it provides comprehensive pan-Arab coverage with fine-grained country-level topics and a unified MCQ benchmark.

in sociological and economic data further demonstrate that model value representations diverge from those of target populations, and that decisions in culturally situated scenarios only partially align with human judgments across regions (Dokic et al., 2025; Song et al., 2025; Khan et al., 2025; Naous et al., 2024). While these works provide important insights into cultural misalignment, they are largely diagnostic in nature and do not offer direct mechanisms for improving alignment.

Preference-based cultural alignment. Preference-based supervision offers a direct means of aligning language models with culturally situated behavioral expectations. Methods such as Reinforcement Learning from Human Feedback, DPO (Rafailov et al., 2023), and Demonstration Iterated Task Optimization (DITTO) (Shaikh et al., 2025) optimize models using human comparisons among candidate responses. Recent datasets have begun to extend preference learning beyond generic, English-centric interactions. CARE (Guo et al., 2025) provides multilingual, human-annotated preference judgments for culturally situated responses, including Arab contexts. IndoPref (Wiyono et al., 2025) introduces a native Indonesian, human-authored pairwise preference dataset across multiple domains, while PRISM (Kirk et al., 2024) connects fine-grained preference feedback with the demographic characteristics and stated values of participants from diverse countries. However, these resources differ in their alignment targets: IndoPref primarily focuses on response naturalness and quality, whereas PRISM emphasizes subjective and individualized preferences rather than explicit culture-specific behavioral norms. Moreover, CARE remains limited in scale and does not provide comprehensive pan-Arab coverage or a unified evaluation benchmark.

Consequently, existing resources tend to support either culturally grounded instruction and evaluation or general and multicultural preference learning, leaving large-scale preference-based cultural alignment—particularly for Arabic and the wider Arab world—underexplored.

3 ARABPREF

We design ARABPREF around country–aspect pairs because cultural norms vary by locale and social context. Preference pairs capture contrastive behavioral judgments, while MCQs evaluate whether models can recognize culturally appropriate behavior among plausible alternatives. ARABPREF has two components: a preference dataset and a multiple-choice question (MCQ) dataset. Figure 1 illustrates the samples. To construct datasets, we generate rudimentary preference data (Section 3.1). We refine the preference dataset through human annotation (Section 3.2) and generate the MCQ dataset for evaluation (Section 3.3).

3.1 Rudimentary Preference Data

Arab League Countries This stage aims to construct a behavioral preference dataset covering the 22 member states of the Arab League[1]. Each country possesses a distinct cultural and historical background, which translates into nuanced behavioral patterns in real-world applications.

Cultural Categories This stage establishes cultural categories before generating preference data. All extracted categories undergo manual review to ensure contextual appropriateness and cultural relevance. We obtain 16 cultural categories, including social etiquette, business and work, and religion and rituals, expanding them into 200 aspects. Humans verify all categories and aspects. A list of aspects for each category appears in Appendix A.3.

[1] https://en.wikipedia.org/wiki/Arab_League

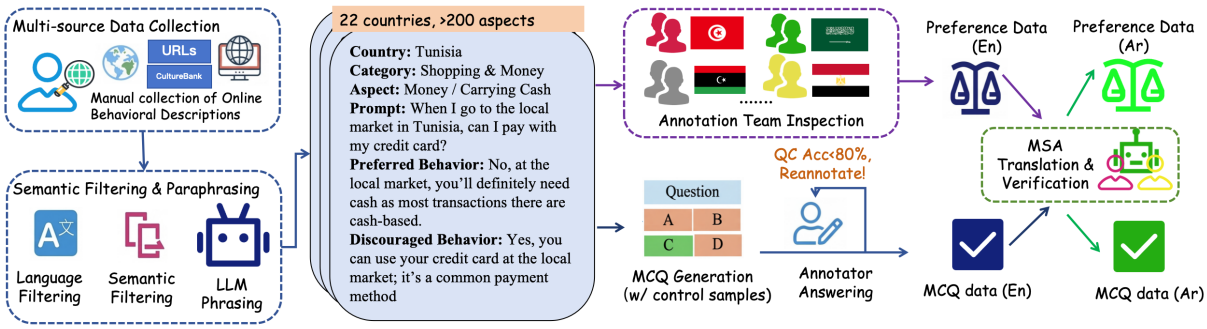

Figure 2: Overview of the data curation and validation pipeline. Our process begins with the manual collection of cultural behavioral descriptions from diverse online sources and URLs, supplemented by CultureBank. After automated semantic filtering and paraphrasing, the data undergoes a rigorous Human-in-the-loop (HITL) validation phase. Annotators perform an inspection to ensure cultural authenticity. For the MCQ generation, a Quality Control (QC) loop is implemented where samples with low accuracy are re-annotated. Finally, the data is translated into MSA and verified to produce the final bilingual Preference and MCQ datasets.

Preferred and Discouraged Behaviors The dataset is constructed through a multi-stage pipeline, as illustrated in Figure 2. First, we aggregate behavioral data from two primary sources: (i) manually filtered web-based resources [2] and (ii) entries from the CultureBank (Shi et al., 2024). All raw data are originally in English. We then process these sources to extract distinct country–aspect pairs and split these pairs into disjoint training and test sets before paraphrase generation.

For each country–aspect pair, we use Gemini-2.5-Flash to paraphrase pairs of preferred and discouraged behaviors using the cultural sources as context. We then apply automated filters: language validation, structural de-duplication via the `MinHash` algorithm (Broder, 1997), and semantic overlap removal (see Appendix A.1). To ensure that these contrasts capture cultural nuances and correct potential model hallucinations, we implement a Human-in-the-Loop (HITL) annotation process.

3.2 Preference Dataset Generation

To refine the rudimentary preference data described in Section 3.1, we conducted a large-scale human annotation project with a professional linguistic service provider. This ensures the dataset captures authentic cultural nuances and maintains high linguistic quality in the 22 target countries. The preference generation follows a multi-stage HITL framework, including cultural preference validation and MSA verification. We describe the full quality-control procedure in Section 3.4.

[2]We use travel blogs and official travel recommendations from embassies; a full list with descriptions is given in Appendix A.2

3.3 MCQ Generation

Based on the validated preference aspects, we generate MCQs to evaluate a model's ability to distinguish culturally appropriate behaviors. Importantly, we split the data at the country–cultural-aspect level before generating preference paraphrases. Preference instances used for training are derived exclusively from the training country–aspect pairs, whereas MCQs are constructed only from held-out country–aspect pairs in the test split. Consequently, no training prompt, chosen response, or rejected response is reused as an MCQ stem or answer option.

Distractor Selection and Refinement For each *country–aspect* pair, we create MCQs using predefined templates with scenario-specific details. To construct challenging MCQs, the target behavior serves as the *correct answer*, while three *distractors* are generated: one representing the opposite behavior (inverse polarity) within the same country, and two representing behaviors from the same aspect but associated with different countries. We then apply semantic filtering to ensure that the answer choices are sufficiently distinct. (Appendix A.1) and a specific LLM prompt to ensure language neutrality (Appendix H). This ensures that the model must distinguish within a specific cultural context and that its choices do not overlap with the training data.

Human-in-the-Loop Validation The annotation team described in Section 3.2 performed a final validation of the MCQs. To ensure reliability, we randomly inserted quality control (QC) samples into the workflow.

Country	Pref Train		Pref Test		MCQ	
	En	Ar	En	Ar	En	Ar
Egypt	1219	1219	329	329	62	62
Morocco	1114	1114	226	159	59	59
Saudi Arabia	972	972	141	141	52	52
Algeria	958	958	165	131	50	50
Jordan	924	924	254	202	72	72
Lebanon	907	907	199	198	39	39
Tunisia	860	860	317	308	61	61
Yemen	758	758	189	162	62	62
Syria	757	757	128	117	35	35
UAE	720	720	159	156	49	49
Palestine	679	679	135	135	46	46
Libya	628	628	114	79	27	27
Iraq	598	598	135	127	28	28
Oman	572	572	134	102	40	40
Sudan	564	564	80	80	28	28
Bahrain	545	545	147	134	41	41
Qatar	517	517	104	86	49	49
Somalia	488	488	32	31	43	43
Kuwait	476	476	82	81	43	43
Djibouti	436	436	51	41	41	41
Comoros	421	421	82	82	31	31
Mauritania	417	417	97	83	34	34
Total	**15530**	**15530**	**3300**	**2964**	**992**	**992**

Table 2: Statistics of the ArabPref dataset, including English and Arabic preference data and MCQ coverage across 22 Arab League countries. Where the test preferences and MCQs are verified by human annotators.

Annotators were required to maintain a minimum accuracy of 80% on these QC items to be considered valid. Following the validation of the English MCQs, we utilized an LLM for initial MSA translation, followed by a final round of human post-editing to guarantee technical and cultural flawlessness. The whole annotation guideline is in Appendix I.

3.4 Quality Check

Validation safeguards To ensure that ARABPREF reflects culturally grounded behavior rather than unverified model-generated content, we implement validation safeguards throughout the annotation pipeline for test preference data and MCQs. All test preference and MCQ data are reviewed by a team of 40 specialized annotators, with 2–3 experts assigned to each target country to provide country-specific cultural knowledge. We enforce a Native-In-Country policy whenever possible: 95% of annotators reside in their native countries, while the remaining 5% are native speakers who have lived in the target region for over 15 years. This composition helps ground validation decisions in linguistic competence and familiarity with local norms.

The preference data undergo a two-stage HITL protocol. In the first stage, *Cultural Preference Validation*, annotators review English prompt-chosen-rejected triples and verify whether the chosen and rejected responses genuinely reflect preferred and discouraged behaviors in the target country's cultural context. In the second stage, *MSA Verification*, native speakers verify the MSA translations for fluency, naturalness, and semantic alignment with the original English source, while filtering out unqualified translations. For MCQ validation, annotation quality is monitored through randomly inserted quality-control samples, and annotators are required to maintain at least 80% accuracy on these items. Batches showing low engagement, such as indiscriminate acceptance, minimal edits, or lack of meaningful revisions, are flagged for manual review and, when necessary, escalated to senior linguistic experts. After that, as suggested by annotators, some MCQs are reduced to three answer options to avoid cases in which multiple answers could be considered correct. Finally, a 10% subsample of the annotated data undergoes secondary expert verification.

For preference data, this process yields a raw agreement rate of 90.1%, indicating strong inter-annotator concordance. For MCQ data, inter-annotator agreement yields a Cohen's κ of 0.693, indicating substantial agreement (Landis and Koch, 1977). In addition, 15.25% of the originally collected English cultural preference candidates are rejected by human annotators, while a further suggestion that human validation substantially reshapes the automatically generated candidates rather than merely approving them. The final data distribution is summarized in Table 2.

3.5 Cultural Differences

ARABPREF is explicitly designed to capture the substantial cultural heterogeneity within the Arab world. For *Alcohol*, preferred responses range from strict prohibition (*Saudi Arabia*, *Libya*) through venue-restricted permissibility (*UAE*, *Jordan*) to comparatively liberal norms in *Lebanon*. Similarly, *Business Dress Codes* range from traditional attire, such as the thobe and turban in *Yemen* or the abaya in *Saudi Arabia*, to conservative Western-style clothing in *Algeria* and *Egypt*. *Public Affection* follows a similar gradient: while *Egypt* and *Syria* advise against hand-holding, *Lebanon* and *Tunisia* (specifically in urban areas) mark it as acceptable. Details are available in Appendix A.5.

Model & Method	English (En)				Arabic (Ar)			
	Cultural	General	Literacy	Avg.	Cultural	General	Literacy	Avg.
Llama-3.1-8B-instruct								
Vanilla	3.23	3.35	3.63	3.40	3.13	3.24	3.07	3.15
w/ PALM (SFT)	3.74*	3.92*	**4.08***	3.91*	3.36*	3.49*	**3.88***	3.58*
w/ CARE (DPO)	3.85*	4.08*	3.83*	3.92*	3.24*	3.38*	3.27*	3.30*
w/ CARE (KTO)	3.66*	3.82*	3.69*	3.72*	3.17	3.31*	3.08	3.19
w/ ARABPREF (DPO)	3.78*	3.96*	3.61	3.78*	3.49*	3.66*	3.63*	3.59*
w/ ARABPREF (KTO)	3.95*	4.15*	3.58*	3.89*	3.50*	3.68*	3.08	3.42*
w/ ARABPREF +CARE (DPO)	3.78*	3.97*	3.97*	3.91*	**3.76***	**3.94***	3.36*	**3.69***
w/ ARABPREF +CARE (KTO)	3.85*	4.05*	3.76*	3.89*	3.37*	3.54*	3.15*	3.35*
w/ ARABPREF +CARE (SFT)	**4.12***	**4.32***	3.67	**4.04***	3.36*	3.52*	2.89*	3.26*
Qwen-2.5-7B-Instruct								
Vanilla	3.41	3.58	4.07	3.69	3.89	4.08	3.98	3.98
w/ PALM (SFT)	4.02*	4.28*	4.57*	4.29*	3.36*	3.53*	3.68*	3.52*
w/ CARE (DPO)	**4.28***	4.55*	4.06	4.30*	4.21*	4.46*	3.66*	4.11*
w/ CARE (KTO)	4.11*	4.37*	4.00*	4.16*	4.19*	4.44*	3.57*	4.07*
w/ ARABPREF (DPO)	4.26*	4.53*	4.43*	4.41*	4.01*	4.25*	3.81*	4.02
w/ ARABPREF (KTO)	4.33*	4.60*	4.71*	4.55*	**4.33***	**4.59***	4.22*	4.38*
w/ ARABPREF +CARE (DPO)	**4.38***	4.31*	3.86*	4.18*	4.27*	4.53*	3.94*	4.25*
w/ ARABPREF +CARE (KTO)	4.19*	**4.69***	3.53*	4.14*	4.32*	4.58*	**4.51***	**4.47***
w/ ARABPREF +CARE (SFT)	4.36*	4.67*	**4.72***	**4.58***	3.94*	4.18*	2.60*	3.57*
Jais-adapted-7b-chat								
Vanilla	3.41	3.58	4.22	3.74	3.40	3.57	3.64	3.54
w/ PALM (SFT)	3.18*	3.34*	3.95*	3.49*	3.26*	3.42*	3.74*	3.47*
w/ CARE (DPO)	3.99*	4.23*	4.31*	4.18*	3.36*	3.56	4.20*	3.71*
w/ CARE (KTO)	3.28*	3.44*	4.20	3.64*	3.37	3.54	3.84*	3.58
w/ ARABPREF (DPO)	4.33*	4.59*	4.68*	4.53*	4.24*	4.49*	**4.21***	4.31*
w/ ARABPREF (KTO)	3.42	3.59	4.06*	3.69*	3.62	3.80*	3.89*	3.77*
w/ ARABPREF +CARE (DPO)	4.39*	4.65*	**4.77***	4.60*	4.28*	4.54*	4.20*	4.34*
w/ ARABPREF +CARE (KTO)	3.52*	3.70*	4.37*	3.86*	3.86*	4.09*	3.81*	3.92*
w/ ARABPREF +CARE (SFT)	**4.50***	**4.77***	4.58*	**4.62***	**4.42***	**4.68***	4.20*	**4.43***
Proprietary models (zero-shot)								
DEEPSEEK-V4-FLASH	4.80	4.56	4.78	4.71	4.76	4.74	4.80	4.77
QWEN3.6-PLUS	4.75	4.83	4.71	4.76	4.74	4.63	4.61	4.66
CLAUDE-SONNET-4	4.91	4.85	4.99	4.92	4.87	4.36	4.50	4.58

Table 3: Preference-alignment results in English and Arabic, evaluated using an LLM-as-a-judge framework along three dimensions: Cultural Appropriateness, General Quality, and Literacy. All values are scores on a 1–5 Likert scale. Cell colors indicate changes relative to the corresponding Vanilla model: green denotes improvement and red denotes degradation, with darker shades representing larger absolute changes. The best result for each model is highlighted in **bold**. Asterisks on the changes indicate statistically significant differences from the corresponding vanilla model ($p < 0.05$) through two-sided paired permutation tests. Proprietary models are evaluated in a zero-shot setting.

4 Arabic Cultural Behavior Alignment

4.1 Alignment Methods

We employ three post-training alignment methods: Supervised Fine-Tuning (SFT), Direct Preference Optimization (DPO) (Rafailov et al., 2023), and Kahneman–Tversky Optimization (KTO) (Ethayarajh et al., 2024). These methods cover complementary supervision signals, including direct response imitation, pairwise preference learning, and binary preference optimization. In addition, to investigate sampling efficiency, we include Demonstration-Driven Iterative Training with Preference Optimization (DITTO) (Shaikh et al., 2025). This setup allows us to compare different alignment objectives and examine their effects on culturally appropriate behavior. Detailed method formulas are provided in Appendix D, while the sampling-efficiency experiments are reported in Appendix E.

4.2 Experiment Setup

Baselines We evaluate a diverse range of LLMs categorized into three distinct groups: (1) **Multilingual Models**, including Llama-3.1-8B-Instruct (Grattafiori et al., 2024) and Qwen-2.5-7B-Instruct (Qwen et al., 2025); (2) **Arabic-centric Models**, represented by Jais-Adapted-7B-Chat (Sengupta et al., 2023; Inception, 2024);

and (3) **Proprietary Models**, including DeepSeek-V4-Flash (DeepSeek-AI et al., 2026), Qwen3.6-Plus (Yang et al., 2025), GPT-5.4 (Singh et al., 2026) and Claude-Sonnet-4 (Anthropic, 2025).

Alignment Data We use the preference training data of our proposed ARABPREF dataset for cultural alignment. We also incorporate the CARE dataset (Guo et al., 2025), which is a multilingual preference dataset spanning Chinese, Japanese, and Arabic cultures. We select the Arabic portion of CARE for reinforcement learning. Furthermore, we use PALM (Alwajih et al., 2025), a comprehensive, human-created Arabic instruction dataset, from which we choose the MSA portion for fine-tuning.

Evaluation Metrics To quantify the cultural alignment and linguistic quality of model generations, we employ an *LLM-as-a-judge* framework. We utilize GPT-4o (OpenAI et al., 2024) as a backbone evaluator, guided by a multi-dimensional rubric specifically designed to capture the nuances of cultural behavior following Guo et al. (2025). Each response is scored on a Likert scale (1–5) across three primary criteria, cultural appropriatenesss, general quality, and literacy. A detailed description of the metrics and scoring can be found in Appendix C. We also ask humans to annotate the responses; the Spearman's correlation between human scoring and machine scoring is available in Appendix F, showing a strong Spearman's correlation exceeding 0.60 between human and machine annotations. A stability analysis of LLM-as-a-judge evaluation is available in Appendix G.

4.3 Preference Generation

Table 3 summarizes the preference-generation results from the LLM-as-a-judge evaluation. Preference alignment improves the open-source models overall, but the gains vary across models, methods, and languages. Jais shows the most consistent improvement. With ARABPREF +CARE SFT, its English average score increases from 3.74 to 4.62, and its Arabic average score increases from 3.54 to 4.43. In contrast, Qwen achieves its best English average score with ARABPREF +CARE SFT (4.58), but its Arabic average score drops from 3.98 to 3.57, mainly because its Literacy score decreases from 3.98 to 2.60. ARABPREF +CARE KTO instead gives Qwen the highest Arabic average score of 4.47. Llama also improves mainly in English, while its best Arabic average score is 3.69 with ARABPREF +CARE DPO. These results show that no single alignment method consistently benefits all models and languages.

Model & Method	English (En)		Arabic (Ar)	
	Acc.	Δ	Acc.	Δ
Jais-adapted-7B-chat				
Vanilla	49.6	–	39.4	–
w/ PALM (SFT)	40.4	↓ 9.2	37.1	↓ 2.3
w/ CARE (DPO)	51.0	↑ 1.4	**45.6**	↑ **6.2**
w/ CARE (KTO)	50.0	↑ 0.4	40.1	↑ 0.7
w/ ARABPREF (DPO)	52.6	↑ 3.0	40.2	↑ 0.8
w/ ARABPREF (KTO)	51.7	↑ 2.1	41.8	↑ 2.4
w/ ARABPREF +CARE (DPO)	**53.7**	↑ **4.1**	43.1	↑ 3.7
w/ ARABPREF +CARE (KTO)	51.3	↑ 1.7	42.4	↑ 3.0
Qwen-2.5-7B-Instruct				
Vanilla	63.3	–	57.6	–
w/ PALM (SFT)	63.0	↓ 0.3	56.9	↓ 0.7
w/ CARE (DPO)	67.5	↑ 4.2	57.6	↑ 0.0
w/ CARE (KTO)	66.2	↑ 2.9	57.8	↑ 0.2
w/ ARABPREF (DPO)	67.0	↑ 3.7	58.0	↑ 0.4
w/ ARABPREF (KTO)	66.4	↑ 3.1	57.5	↓ 0.1
w/ ARABPREF +CARE (DPO)	**68.6**	↑ **5.3**	**58.7**	↑ **1.1**
w/ ARABPREF +CARE (KTO)	67.1	↑ 3.8	58.3	↑ 0.7
Proprietary models (zero-shot)				
DEEPSEEK-V4-FLASH	75.3	–	71.6	–
QWEN3.6-PLUS	**80.5**	–	**76.5**	–
GPT-5.4	79.2	–	75.9	–
CLAUDE-SONNET-4	74.8	–	73.7	–

Table 4: MCQ accuracy (%) on the English and Arabic datasets. Δ denotes the absolute change relative to the corresponding Vanilla model. For each open-source model, the best result is shown in bold and the second-best result is underlined. Proprietary models are evaluated in the zero-shot setting.

The zero-shot proprietary models provide a reference for the open-source systems. Claude Sonnet 4 achieves the highest English average (4.92), followed by Qwen3.6-Plus (4.76) and DeepSeek-V4-Flash (4.71). In Arabic, DeepSeek-V4-Flash ranks first at 4.77, ahead of Qwen3.6-Plus (4.66) and Claude Sonnet 4 (4.58). The best open-source averages are 4.62 for Jais in English and 4.47 for Qwen in Arabic. Although the proprietary models score higher on average, the differences are modest for DeepSeek-V4-Flash in English and Claude Sonnet 4 in Arabic. Results vary by dimension. Jais matches or exceeds DeepSeek-V4-Flash on English General Quality (4.77 vs. 4.56), and Qwen outperforms Qwen3.6-Plus and Claude Sonnet 4 on Arabic General Quality (4.68 vs. 4.63 and 4.36). Proprietary models obtain the highest Cultural Appropriateness scores in both languages. These zero-shot results are reference points rather than direct comparisons of alignment methods.

4.4 MCQ Answering

Results in Table 4 show that the effect of alignment varies across models and languages. SFT provides limited benefits and can even reduce ac-

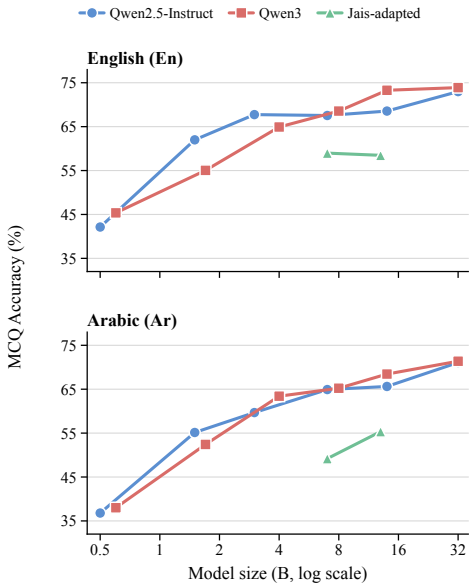

Figure 3: Scaling behavior on the ARABPREF MCQ benchmark. The upper and lower panels report accuracy on the English (En) and Arabic (Ar) test sets, respectively. Results are shown for Qwen2.5-Instruct, Qwen3, and Jais-adapted models across different model sizes. Each language contains 992 questions.

curacy, whereas DPO and KTO generally perform better on the structured MCQ task.

ARABPREF +CARE DPO produces the largest gains for Qwen, increasing accuracy by +5.2 points in English and +1.1 points in Arabic, and improves Jais by +3.7 points in Arabic. Jais also shows a larger Arabic gain under CARE DPO (+6.2) than Qwen, despite starting from a lower baseline. Combining CARE with ARABPREF gives the best overall performance, reaching 68.6% English accuracy for Qwen. These results suggest that general preference data and culturally focused data provide complementary benefits, although the resulting gains are not consistent across models and languages.

5 Discussion

Scaling We examine scaling across the Qwen2.5, Qwen3 (Yang et al., 2025), and Jais-adapted model families. Figure 3 shows that MCQ accuracy generally increases with model size, although the pattern varies by model family and language. Both Qwen2.5-Instruct and Qwen3 improve rapidly at smaller scales, with gains becoming more gradual beyond the 3–8B range. Qwen3 performs best at 32B, reaching 73.9% in English and 71.4% in Arabic, slightly above Qwen2.5-Instruct on the same scale. Jais-adapted shows a different pattern: scaling from 7B to 13B increases accuracy for Arabic from 49.2% to 55.3%, but not for English.

English accuracy is consistently higher than Arabic accuracy across all three model families. This gap may reflect the stronger representation of English in pretraining data. At 32B, both Qwen model series approach the performance of the proprietary reference models. Overall, scaling improves culturally grounded MCQ performance, but model architecture and language coverage remain important factors.

Head-to-head win rates. Figure 4 compares models trained on ARABPREF +CARE with their CARE-only (DPO) or PALM (SFT) counterparts, using GPT-4o for pairwise evaluation. Under DPO, the ARABPREF +CARE models receive more wins in five of the six model-language comparisons. The largest difference is observed for Jais in English, with 58.5% wins for ARABPREF +CARE and 30.3% for CARE-only. Jais in Arabic is the exception: CARE-only receives more wins than ARABPREF +CARE (49.6% vs. 42.6%). Under SFT, ARABPREF +CARE is preferred in all six comparisons, although the difference for Qwen in English is small (48.2% vs. 46.3%). The largest SFT gains are again observed for Jais, which receives 82.8% wins in English and 59.2% in Arabic. These results indicate that ARABPREF can complement CARE and PALM, but its effect varies across training objectives, models, and languages.

Model	Language	Training Data		
		English	Arabic	Whole
Llama	En	3.53	3.47	3.78
	Ar	3.17	3.08	3.59
Qwen	En	4.56	4.63	4.41
	Ar	4.10	3.96	4.02
Jais	En	4.34	4.30	4.53
	Ar	4.20	4.14	4.31

Table 5: Model performance comparison with monolingual versus whole-dataset training in preference generation. Cell colors compare English and Arabic training against the corresponding Whole-training score. Green indicates an improvement, red indicates a decrease, and darker shades indicate larger absolute differences.

Monolingual vs. Multilingual Training The results demonstrate that the impact of training data composition is highly architecture-dependent. For Llama and Jais, the whole dataset consistently yields peak performance across both English and

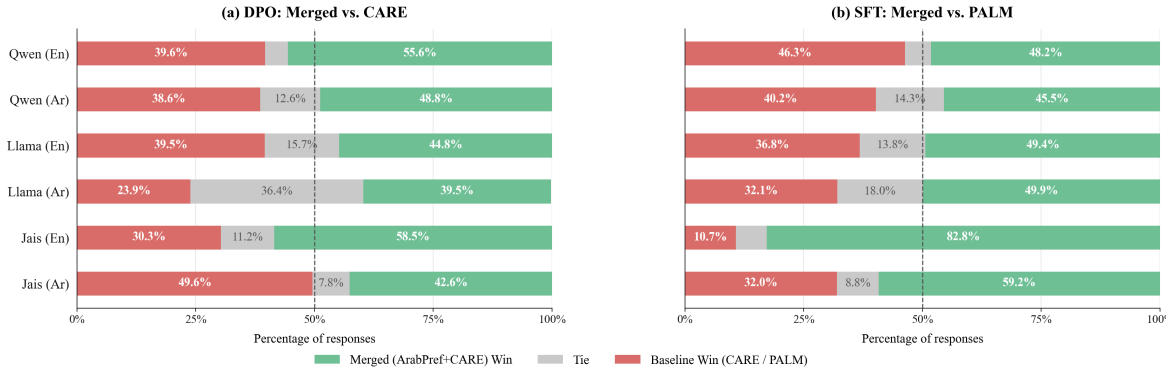

Figure 4: Head-to-head win rate comparisons evaluated by GPT-4o as judge. Each bar shows the win percentage of the respective system relative to the 50% midpoint. (a) DPO training: our merged dataset (ARABPREF +CARE) vs. CARE-only across three base models and two languages (Ar/En). (b) SFT training: merged dataset vs. PALM. Results show that the merged dataset consistently achieves competitive or superior win rates, demonstrating that the observed gains generalise beyond vanilla baselines.

Arabic, suggesting these architectures benefit from cross-lingual transfer and broader cultural context.

In contrast, the Qwen model exhibits a specialized sensitivity to data language: it achieves its higher score for English and Arabic via English-only training, with the combined dataset leading to marginal performance declines across both English and Arabic. This indicates that while architectures like Llama and Jais thrive on diverse multilingual exposure, Qwen is more susceptible to interference between language-specific specialization and the general-purpose distribution of the full corpus. Discussion on sampling efficiency is available in Appendix E.

6 Conclusion and Future Work

The paper introduces ARABPREF, a culturally grounded preference dataset covering 22 Arab countries, 16 categories, and 200 aspects. Post-training experiments show that models trained on ARABPREF achieve stronger cultural alignment. By supporting both training and evaluation, ARABPREF advances culturally aware Arabic language modeling and helps models reflect regional values and norms. Future work will expand coverage of regional dialects, code-switching, under-represented subcultures, and within-country variation; track how preferences evolve over time; and evaluate multi-turn interactions shaped by speaker relationships, social settings, and conversational history. Broader annotator coverage and longitudinal data could further distinguish shared norms from context-specific preferences without homogenizing national cultures.

Limitations

While ARABPREF provides comprehensive coverage of cultural preferences across 22 Arab countries, it may not capture the full cultural diversity within each nation, especially at the regional or local level. The focus on behavioral preferences may overlook other important cultural dimensions, such as emotional expression, non-verbal communication, or specific context-dependent behaviors. Moreover, although the MCQ-based evaluation framework offers useful insights, it may not fully capture the complexity of cultural alignment in more dynamic, open-ended, or real-world scenarios where models need to respond flexibly to diverse and evolving cultural contexts. As such, further research is needed to develop more nuanced evaluation methodologies and expand the dataset to address these gaps.

Ethics and Broader Impact

The development and use of ARABPREF aim to enhance cultural alignment in Arabic language models, promoting more respectful and accurate interactions across diverse Arab contexts. However, it is important to acknowledge that cultural behaviors are dynamic and diverse, and any dataset, including ARABPREF, can only represent a portion of the full spectrum of cultural practices. Ethical considerations must be taken into account when deploying these models, especially to avoid reinforcing stereotypes or biases. Furthermore, ongoing efforts are needed to ensure the dataset reflects evolving cultural norms and values, with an emphasis on inclusive and sensitive data collection.

Acknowledgments

We thank the anonymous reviewers for their constructive feedback during the review process. This research was partially supported by the Dubai Research, Development and Innovation (RDI) Grant[3] and the MBZUAI supercomputing cluster.

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A Data Generation

A.1 Semantic Filtering

Automated Filtering Steps in Preference Generation We apply three sequential filtering stages to the generated preference pairs. First, Language Validation ensures all entries are strictly in English. Second, Near-Duplicate Removal utilizes the `MinHash` algorithm (Broder, 1997) to eliminate structural redundancies. Finally, we perform Semantic Deduplication by encoding behaviors with *GemmaEmbedding* (Vera et al., 2025) and calculating cosine similarity. After evaluating thresholds in the range $\{0.70, \ldots, 0.95\}$ via manual inspection, we select 0.90 for the preference dataset to balance diversity and preservation, while a stricter threshold of 0.80 is applied to the MCQ data to ensure options remain clearly distinguishable. This pipeline yields a high-quality corpus of 15,530 training and 3,894 raw test samples in English.

Semantic Similarity Filtering in MCQ Generation: To ensure that the four choices are not semantically similar, we use GemmaEmbedding and set a similarity threshold of 0.80. If the similarity between any two choices exceeds the threshold, we replace one of the distractor countries and select a new choice. This process continues until no pair of choices exceeds the threshold. The test splits of preference data are deliberately constructed to mirror MCQ's (country, category, aspect) combinations while the training preference data has much broader, non-overlapping coverage.

A.2 Used Web-Resources

We compile cultural etiquette guidance from publicly available online sources covering 13 countries (Saudi Arabia, United Arab Emirates, Yemen, Jordan, Lebanon, Syria, Palestine, Egypt, Sudan, Morocco, Algeria, Tunisia, and Libya), plus a small set of region-wide (Arab World) references. The sources include travel blogs and culture/etiquette guides, complemented by official travel recommendations and advisories from government and embassy-affiliated services (e.g., the U.S. Department of State, the UK FCDO, the Government of Canada). URLs are provided in Table 6.

A.3 Categories description and statistics

This appendix clarifies each culture-related category used in our annotations. Each category captures culturally grounded norms, expectations, or constraints that may vary across Arab countries.

Social Etiquette Every day interpersonal norms in public and social interactions, such as forms of greeting, appropriate topics of conversation, respectful address, queuing behavior, and when it is acceptable to refuse or accept an offer.

Hospitality & Home Life Practices and expectations around visiting, hosting, and household life, including guest treatment, entering homes, seating arrangements, gift-giving, and norms around privacy and family space.

Religion & Rituals Religious practices and observances that shape daily life, such as prayer times, fasting periods, religious holidays, visiting places of worship, and behaviors considered respectful or disrespectful in religious contexts.

Dining & Food Customs and etiquette related to eating and shared meals (how to eat rather than what to eat), such as waiting for the host to start, eating with the right hand, using bread to scoop food, and expectations around sharing dishes.

Business & Work Workplace and professional norms, including meeting etiquette, negotiation style, hierarchy and titles, punctuality expectations, communication formality, and norms around work hours or availability.

Modern & Technology Cultural norms around photography, social media, privacy, and device use in public or formal settings.

Gender & Travel Gender-specific norms and rules relevant to travelers, such as clothing expectations for women, gender segregation in certain venues, and guidance on mixed-gender interactions in public or private settings.

Family & Children Norms centered on family structure, roles, and interactions with children, including respect for elders, family decision-making, acceptable behavior around children, and expectations for family-oriented settings.

Health & Environment Cultural practices tied to health, hygiene, and environmental context, such as attitudes toward heat and hydration, norms around cleanliness, public health expectations, and locally relevant environmental considerations.

Politics & Law Norms and constraints shaped by legal or political context, including sensitive topics to avoid, restrictions on speech or behavior, and locally specific rules that visitors should be aware of.

Shopping & Money Norms related to commerce and payments, such as bargaining customs, tipping expectations, appropriate conduct in markets, and payment preferences (cash vs. card) where culturally relevant.

Charity & Society Social responsibility norms, including charitable giving practices, community support expectations, volunteering, and culturally grounded concepts of generosity and mutual aid.

Personal Appearance Expectations around dress and grooming in different contexts (e.g., modesty norms, acceptable swimwear in certain settings, or formality levels), distinct from explicitly gender-specific travel rules.

Transport Norms and rules specific to getting around, such as women-only metro cars, seating expectations, etiquette in taxis or ride-hailing, and behavior on public transport.

Pets & Environment Cultural attitudes and practical norms involving animals in daily life, such as expectations about dogs in public spaces, interactions with stray animals, and where pets are typically welcomed or not.

Safety Safety guidance, including norms that reduce risk (e.g., situational awareness expectations), locally sensitive areas or behaviors, and advice shaped by context rather than general travel tips.

Country	Sources
Saudi Arabia	S1, S2, S3, S4, S5
United Arab Emirates	UAE1, UAE2, UAE3, UAE4, UAE5, UAE6, UAE7
Yemen	Y1, Y2, Y3, Y4, Y5, Y6
Jordan	J1, J2, J3, J4, J5, J6
Lebanon	L1, L2, L3, L4, L5, L6, L7
Syria	SY1, SY2, SY3, SY4, SY5, SY6, SY7
Palestine	P1, P2, P3, P4, P5, P6, P7, P8
Egypt	E1, E2, E3, E4, E5, E6, E7, E8
Sudan	SU1, SU2, SU3, SU4, SU5, SU6
Morocco	M1, M2, M3, M4, M5, M6, M7, M8, M9, M10, M11, M12
Algeria	A1, A2, A3, A4, A5, A6, A7, A8
Tunisia	T1, T2, T3, T4, T5, T6, T7, T8
Libya	LI1, LI2, LI3, LI4, LI5, LI6, LI7, LI8, LI9
Arab World (Generic)	AR1, AR2, AR3, AR4, AR5

Table 6: List of travel etiquette and travel-advisory sources used in our work.

Figure 5 provides summary statistics of the number of aspects for each category. The aspects for each category is listed in Table 9.

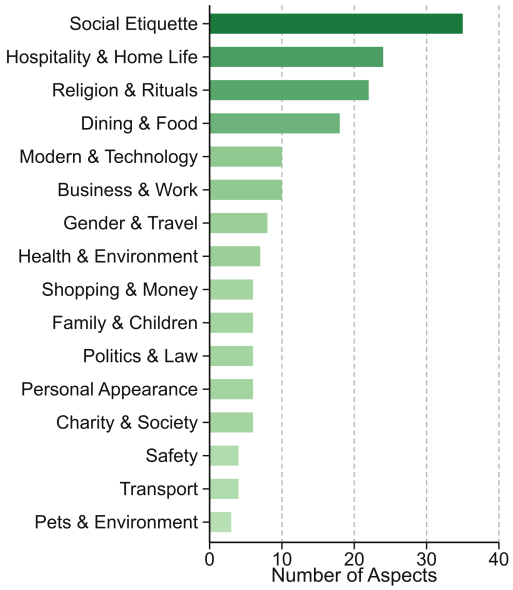

Figure 5: A statistics of the number of aspects for each cultural category in ARABPREF.

Country	Train	Test (Raw)	Test (Filtered)
Egypt	1219	329	329
Morocco	1114	237	226
Saudi Arabia	972	160	141
Algeria	958	225	165
Jordan	924	257	254
Lebanon	907	207	199
Tunisia	860	405	317
Yemen	758	205	189
Syria	757	172	128
UAE	720	183	159
Palestine	679	153	135
Libya	628	119	114
Iraq	598	144	135
Oman	572	135	134
Sudan	564	99	80
Bahrain	545	148	147
Qatar	517	109	104
Somalia	488	144	32
Kuwait	476	106	82
Djibouti	436	137	51
Comoros	421	109	82
Mauritania	417	111	97
Total	**15,530**	**3,894**	**3,300**

Table 7: Statistics of the English preference dataset across 22 countries, detailing the sample counts for training, raw test, and human-filtered test splits.

A.4 Overall Data statistics

Table 7 shows the number of preference data samples across the training, raw test, and human-filtered test splits for all 22 Arab countries, with human annotators filtering prompt-chosen-reject triples. We ask human annotators to check the cultural appropriateness of each triple to retain the samples that genuinely reflect the local culture.

Table 8 presents the distribution of categories in the preference and MCQ datasets.

A.5 Intra-Arab Cultural Variation Across Shared Aspects

Table 10 illustrates how preferred norms diverge systematically across Arab nations for four aspects shared by 15 or more countries in ARABPREF.

Category	Train	Test (Raw)	Test (Filtered)	MCQ
Social Etiquette	3327	716	605	458
Religion & Rituals	1647	440	336	172
Dining & Food	1553	369	283	214
Hospitality & Home Life	1497	386	325	246
Gender & Travel	745	193	159	98
Personal Appearance	707	170	155	90
Business & Work	691	200	145	98
Shopping & Money	540	150	136	76
Modern & Technology	553	135	119	94
Politics & Law	360	104	100	56

Table 8: Top 10 categories by sample count in the preference dataset across the training, raw test, and human-filtered test splits, along with the sample count in the MCQ dataset.

Despite a shared linguistic and religious tradition, countries exhibit distinct normative stances reflecting unique legal and social contexts.

B Implementation Details

LLM Inference. For open-source LLMs, we use vLLM (Kwon et al., 2023) with temperature 0.7 and top-p 1.0 for preference generation, and temperature 0 for MCQ solving. We set the context and generation limits to 2,048 (max_model_len=2048) and 512 tokens (max_tokens=512), respectively. We evaluate MCQs using lm-evaluation-harness (Gao et al., 2024). These settings standardize the generated outputs and facilitate consistent downstream evaluation. All experiments are conducted on two NVIDIA A100 GPUs, each with 80 GB of memory. For proprietary model and evaluator, we use OpenAI's `gpt-5.4-2026-03-05` and `gpt-4o-2024-11-20`, DeepSeek's `deepseek-v4-flash`, and Alibaba Cloud's `qwen3.6-plus-2026-04-02`.

Licenses

- **Apache 2.0:** Qwen2.5-7B-Instruct (Qwen et al., 2025), Qwen3-8B (Yang et al., 2025) and Jais-Adapted-7B-Chat (Sengupta et al., 2023)
- **Llama Community License:** Llama-3.1-8B-Instruct (Grattafiori et al., 2024).
- **MIT:** DeepSeek-v4-Flash (DeepSeek-AI et al., 2026).
- **OpenAI Services Agreement:** GPT-5.4 (Singh et al., 2026) and GPT-4o (OpenAI et al., 2024).
- **Alibaba Cloud Model Studio Terms:** Qwen3.6-Plus (Yang et al., 2025).
- **Anthropic Consumer Terms of Service:** Claude-Sonnet-4 (Anthropic, 2025).

Training Details We train all models with LoRA (Hu et al., 2021) (rank $= 8$, $\alpha = 16$, applied to all linear modules) using the AdamW (Loshchilov and Hutter, 2019) optimizer ($\beta_1 = 0.9$, $\beta_2 = 0.999$, $\epsilon = 10^{-8}$). We use a per-device batch size of 1 and 8 gradient accumulation steps on 2 GPUs, resulting in an effective batch size of 16. Supervised fine-tuning uses a learning rate of 1×10^{-4}; DPO and KTO use 5×10^{-6}. Each model is trained for 3 epochs with a cosine scheduler, a warmup ratio of 0.1, and a weight decay of 0. For DPO and KTO, we set $\beta = 0.1$. All experiments use BF16 precision and a maximum sequence length of 2048 tokens.

C Evaluation Criterion

Breakdown of the three evaluation metrics are listed as follows:

- **Cultural Appropriateness**: This metric assesses the degree to which a response adheres to the specific norms, values, and social sensitivities of the target locale. A high score indicates that the content is culturally authentic and respectful, while lower scores reflect the presence of stereotypes, cultural misunderstandings, or insensitive references.
- **General Quality**: This metric assesses response quality across three dimensions: factual accuracy, depth of explanation, and relevance. Unlike Cultural Appropriateness, which focuses on locale-specific norms, General Quality evaluates whether the response is correct, sufficiently detailed, and focused without extraneous information. A gold reference answer serves as the evaluation baseline.
- **Literacy**: This dimension evaluates the linguistic fluency, grammatical correctness, and syntactic coherence of the output. It measures whether the model's generation is natural and readable, ensuring that the cultural message is not obscured by stylistic or grammatical errors.

The evaluation criterion for human annotation and prompts for LLM-as-a-judge evaluation can be found in Table 11

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Category (Number of unique aspects)	Aspects
Social Etiquette (42)	Greetings, Names and Titles, Handshakes, Eye Contact, Introductions, Personal Space, Gestures & Hand Gestures, Expressing Thanks, Expressing Refusal, Seating, Joking & Humor, Public Affection, Conversation / Asking Questions, Language Use, Meeting Time / Punctuality, Public Behavior / Street Interactions, Queuing / Queue Etiquette, Communication Style, Using Arabic/French, Touching Others, Greeting with "Salaam Alaikum", Flexible Time / Punctuality, Urban/Rural Dialect Switching, Respect for Elders, Showing Soles of Feet, Right-Hand Use for Giving/Receiving, Avoiding Pointing with Index Finger, Silence and Pauses in Conversation, Indirect Communication / Saving Face, Honor and Shame Sensitivity, Compliments & "Mashallah" Responses, Asking About Family (Rapport-Building), Taboo Topics (politics/sectarian issues), Public Displays of Anger, Loud Laughter in Public, Queue Courtesy for Families/Elders, Greeting Order When Entering a Room, Door Etiquette (who enters first), Avoid Passing Objects Over Someone's Head, Accommodating Left-Handed Guests, Respectful Address to Domestic Workers, Sports Events Etiquette (football matches)
Hospitality & Home Life (25)	Visiting Homes, Shoes in Homes, Invitations, Gifts, Hospitality, Thanking Host, Inviting to Eat, Leaving a Gathering, Hospitality to Strangers, Gift-Giving of Sweets, Home Hospitality Rituals, Role of Host in Welcoming, Visiting the Sick (Get-Well Etiquette), Condolences / Mourning Visits, Serving / Seating Elders First, Guest of Honor Seating, Polite Gift Refusal and Re-offer Ritual, Bringing Dates or Fruit to Hosts, Women's Gatherings (Hareem Majlis), Men's Majlis Etiquette, Incense (Bukhoor) for Guests, Gift Wrapping & Color Preferences, Reciprocity / Return-Gift Norms, Hosting Unannounced Visitors, Sharing Food with Neighbors
Religion & Rituals (24)	Religious Sites, Religious Items, Ramadan, Prayer Times / Friday Observance / Friday Prayers, Public Worship Spaces, Festivals / Holidays, Wedding Etiquette, Friday (Jumu'ah) Observance, Henna Traditions, Saying "Bismillah" Before Eating, Eid al-Fitr Etiquette (Zakat al-Fitr, greetings), Eid al-Adha Etiquette (Qurbani sharing), Removing Shoes in Mosques, Adhan (Call to Prayer) Respect (pausing music), Using "Inshallah / Alhamdulillah" Appropriately, Visiting Shrines / Saints' Tombs, Ramadan: Non-Muslim Daytime Eating Etiquette, Prayer Rooms in Malls/Airports Etiquette, Wudu (Ablution) Facility Etiquette, Visiting Cemeteries Etiquette, Using Honorifics (Sheikh, Hajji), Addressing by Kunya (Abu/Umm), Name Order & "bin/bint", Funeral Attire and Participation
Dining & Food (25)	Table Manners / Dining Etiquette, Bread Etiquette, Food (Dietary Norms), Finishing Food, Tea / Coffee Ritual, Refusing Food / Tea, Street Food, Serving & Drinking Arabic Coffee (Qahwah), Communal Eating from a Shared Dish, Bread is Sacred, Suhoor & Iftar Hosting, Offering Dates Before Meals, Eating with the Right Hand, Using Bread as an Utensil, Serving Elders First (Meals), Accepting Second Helpings, Avoiding Food Waste, Shisha / Hookah Etiquette, Street Coffee/Tea Kiosk Etiquette, Spice/Heat Consideration for Guests, Family Sections in Restaurants, Coffee vs Tea Preference by Region, Fruit Plate Ritual After Meals, Alcohol, Cafés & Coffee Culture
Business & Work (14)	Business Etiquette / Business Cards / Business Attire, Dealing with Officials, Business Gift-Giving, Relationship-First Negotiation Style, Wasta (Networking & Intermediation), Decision-Making Hierarchy, Scheduling Around Prayer/Friday, Polite Persistence in Follow-ups, Business Entertaining (non-alcoholic venues), Acceptable Small Talk Topics, Timing of Gifts in Business (after meeting), Business Card Handling (Arabic side up), Office Visiting Hours & Drop-ins, Formal Greetings in Email/Messaging
Modern & Technology (9)	Mobile Phones, Texting/Messaging, Social Media Etiquette, Smoking Etiquette, Photography of Children, Saving Contact Names with Titles (phones), WhatsApp Voice Notes Etiquette, Livestreaming in Public Etiquette, Sharing Religious Content Online Etiquette
Gender & Travel (9)	Women Travelers, Men Travelers, LGBTQ+ / Queer Travelers, Gender Interaction, Gender-Separate Queues/Sections, Cross-Gender Friendship Boundaries, Chaperoned Socializing, Family vs Mixed Areas at Beaches, Cross-Gender Eye Contact Boundaries
Health & Environment (8)	Drinking Water, Littering / Environment, Sacredness of Water & Fountains, Public Bathhouse Traditions, Water Conservation Norms, Fragrance Sensitivity in Public Spaces, Sauna/Steam Room Gender Separation, Picnic & Park Etiquette
Family & Children (9)	Children / Traveling with Children, Birth Celebration (Aqiqah) Etiquette, Complimenting Children with "Mashallah", Evil Eye (Nazar) Beliefs & Amulets, Elder Care Expectations, Parenting in Public (discipline norms), Visiting New Mothers Etiquette, Adoption & Kinship Care Sensitivities, Birthday Celebration Norms
Politics & Law (5)	Monarchy, Respect for Monarchy & Royal Imagery, National Day Celebrations, Flag Respect and National Symbols, Military Service Respect
Shopping & Money (6)	Carrying Cash, Tourist Pricing, Marketplace Haggling as Social Ritual, Money / Carrying Cash, Shopping / Marketplace Interaction / Bartering, Tipping (Baksheesh)
Charity & Society (7)	Beggars & Street Kids, Charity / Street Giving, Charity (Zakat/Sadaqah) Giving Etiquette, Community Fundraising & Mutual Aid, Recognizing Tribal/Clan Affiliations, Poetry & Oral Storytelling at Gatherings, Camel & Horse Traditions
Personal Appearance (7)	Dress Code, Distinct Traditional Clothing, Mosque & Shrine Dress Expectations, Swimwear & Beach Modesty, Traditional Headwear Norms (keffiyeh/hijab), Tattoos & Piercings Perceptions, Perfume/Oud Use in Social Settings
Transport (4)	Taxi Etiquette, Public Transport / Transport Etiquette, Taxi: Front vs Back Seat Choice, Carpooling & Splitting Costs
Safety (3)	Personal Belongings, Street Harassment, Lost and Found
Pets & Environment (3)	Animals & Pets, Pet Dogs in Public Spaces Acceptability, Compassion Toward Stray Animals
Total	**16 categories and 200 unique aspects**

Table 9: Cultural categories and aspects of ArabPref. The taxonomy contains 16 categories and 200 unique aspects. Duplicate aspect entries in the mapping were counted once.

Aspect	Country	Preferred Norm (paraphrased)	Stance
Alcohol	Saudi Arabia	Strictly prohibited; can lead to severe penalties.	Prohibited
	Kuwait	Strictly prohibited; avoid bringing any alcohol.	Prohibited
	Libya	Illegal; avoid bringing or offering alcohol.	Prohibited
	Algeria	Safest to avoid possession entirely.	Restricted
	UAE	Restricted to licensed venues; drink responsibly.	Licensed only
	Jordan	Acceptable at licensed restaurants and hotels.	Licensed only
	Bahrain	Can enjoy a beer at licensed restaurants/hotels.	Permissible
	Lebanon	Liberal consumption; acceptable in most restaurants.	Liberal
Dress Code	Yemen	Men: thobe and turban; Women: jilbab/abaya.	Traditional
	Saudi Arabia	Women: abaya/hijab advised; conservative throughout.	Conservative
	Iraq	Cover arms and legs; chador in holy cities.	Conservative
	Egypt	Cover shoulders and knees; avoid tight clothing.	Modest Western
	Algeria	Modest professional attire; shoulders/knees covered.	Modest Western
	Lebanon	Smart casual or slightly formal; flexible.	Smart casual
	Tunisia	Modest and respectful; avoid attire that attracts attention.	Smart casual
Affection	Saudi Arabia	Refrain from hand-holding; express affection privately.	Prohibited
	Egypt	Avoid all public displays, including hand-holding.	Prohibited
	UAE	Hand-holding acceptable; hugging discouraged.	Restricted
	Morocco	Respect personal space; exercise discretion.	Restricted
	Tunisia	Hand-holding acceptable for married couples in urban areas.	Conditional
	Lebanon	Hand-holding while walking is generally acceptable.	Permissible
Greetings	Jordan	Stand for elders; warm handshake and inquiry.	Elder-focused
	Kuwait	Rise for elders; wait for elder to initiate contact.	Elder-focused
	Sudan	Men embrace; wait for women to initiate handshakes.	Gender-diff.
	Tunisia	Handshake for men; nod or wait for women's cue.	Gender-diff.
	Lebanon	"Marhaba"; warm handshake and informal welcome.	Informal
	Yemen	General wave or nod acceptable in large gatherings.	Pragmatic

Table 10: Examples of divergent preferred norms across Arab nations for four cultural aspects in `ArabPref`. Preferred responses are condensed from dataset entries. The *Stance* column summarizes the normative position along the observed spectrum.

Score	Cultural Appropriateness	General Quality	Literacy
1	Completely misaligned with the cultural context, containing offensive or highly inappropriate references.	Very incomplete, with critical information missing, making the response unusable.	Very poor fluency, riddled with errors, making the text nearly unreadable or incoherent.
2	Major cultural misunderstandings or insensitive references that impact the overall understanding.	Significant omissions that make the instruction or question difficult to interpret or incomplete.	Multiple errors that hinder readability or cause significant confusion for the reader.
3	Noticeable cultural inconsistencies or slight misinterpretations, but the general meaning remains clear.	Noticeable gaps in information or coverage that leave the instruction or question lacking.	Noticeable errors in grammar, spelling, or structure, but the text is still understandable.
4	Minor cultural inaccuracies that do not significantly affect the overall understanding.	Slightly incomplete, with minor missing details that do not impact the overall understanding.	Minor grammatical or stylistic errors that do not significantly affect readability.
5	Fully aligned with the cultural context, showing deep respect for cultural norms and values.	Fully complete, with no missing information, thoroughly covering the required context.	Perfect fluency, with no errors in grammar, spelling, or structure. The text reads naturally.

Table 11: Evaluation criterion for human annotation and LLM-as-a-judge.

D Alignment Methods

We use supervised fine-tuning (SFT), Direct Preference Optimization (DPO), and Kahneman–Tversky Optimization (KTO) for the full-data experiments. We additionally evaluate Demonstration ITerated Task Optimization (DITTO) in the low-data sample-efficiency study only.

Let x denote a prompt, y a response, and π_θ the policy model. We use $\log \pi_\theta(y \mid x)$ to denote the sequence-level log-probability of y conditioned on x.

SFT. Given a set of demonstrations $\mathcal{D}_{\mathrm{SFT}} = \{(x, y)\}$, SFT minimizes the negative log-likelihood of the target responses:

$$\mathcal{L}_{\mathrm{SFT}}(\theta) = -\mathbb{E}_{(x,y)\sim\mathcal{D}_{\mathrm{SFT}}} \left[\log \pi_\theta(y \mid x)\right]. \quad (1)$$

DPO. For a preference pair (x, y^+, y^-), where y^+ is preferred to y^-, DPO compares the policy with a fixed reference policy π_{ref}. Its objective is

$$\Delta_\theta(x, y^+, y^-) = R_\theta(x, y^+) - R_\theta(x, y^-). \quad (2)$$

$$\mathcal{L}_{\mathrm{DPO}}(\theta) = -\mathbb{E}_{(x,y^+,y^-)}\big[\log \sigma\big(\beta \Delta_\theta(x, y^+, y^-)\big)\big]. \quad (3)$$

where σ is the logistic function and $\beta = 0.1$ controls the strength of the preference objective.

KTO. For each preference pair (x, y^+, y^-), we construct two labeled examples, $(x, y^+, 1)$ and $(x, y^-, 0)$, where 1 and 0 denote desirable and undesirable responses, respectively. In our LoRA implementation, π_{ref} is the base model with the adapter disabled. We define

$$r_\theta(x, y) = \log \pi_\theta(y \mid x) - \log \pi_{\mathrm{ref}}(y \mid x). \quad (4)$$

For a minibatch of size B, we estimate the KTO reference point as

$$\hat{z}_0 = \mathrm{stopgrad}\left[\max\left(0, \frac{1}{B}\sum_{i=1}^{B} r_\theta(x_i, \tilde{y}_i)\right)\right], \quad (5)$$

where $\tilde{y}_i$ is a response cyclically shifted from another example in the same minibatch. The loss for an example with label l is

$$d_\theta(x, y) = \beta\big(r_\theta(x, y) - \hat{z}_0\big). \quad (6)$$

$$\ell_{\mathrm{KTO}}(x, y, l) = \begin{cases} \lambda_+\big[1 - \sigma\big(d_\theta(x, y)\big)\big], l = 1, \\ \lambda_-\big[1 - \sigma\big(-d_\theta(x, y)\big)\big], l = 0. \end{cases} \quad (7)$$

We minimize the minibatch mean of ℓ_{KTO} and use $\beta = 0.1$ and $\lambda_+ = \lambda_- = 1.0$.

DITTO. We use DITTO only in the low-data study. Let $\mathcal{D}_E = \{(x, y_E)\}$ denote the demonstration set. We first obtain an initial policy π_0 by applying SFT to $\mathcal{D}_E$ and keep $\pi_{\mathrm{ref}} = \pi_0$ fixed throughout the subsequent iterations. At iteration t, the current policy π_t generates M responses for each demonstration prompt, producing an online dataset $\mathcal{D}_t$. We construct preference comparisons according to

$$\mathcal{D}_E \succ \mathcal{D}_t \succ \mathcal{D}_{t-1} \succ \cdots \succ \mathcal{D}_0, \quad (8)$$

where $\succ$ denotes that the responses on the left are preferred to those on the right. The resulting comparison set contains online pairs between demonstrations and current outputs, replay pairs between demonstrations and earlier outputs, and inter-model pairs between later and earlier policy outputs.

We update π_t with the DPO objective

$$\Delta_\theta^t(x, y^w, y^l) = R_\theta(x, y^w) - R_\theta(x, y^l). \quad (9)$$

$$\mathcal{L}(\theta) = -\mathbb{E}_{(x,y^w,y^l)\sim\mathcal{C}_t}\big[\log \sigma\big(\alpha \Delta_\theta^t(x, y^w, y^l)\big)\big]. \quad (10)$$

where $\mathcal{C}_t$ is the comparison set at iteration t, y^w and y^l are the preferred and dispreferred responses, respectively, and α is the DPO temperature. We report DITTO only as a sample-efficiency analysis because it is designed for adaptation from a small number of demonstrations rather than full-data post-training.

E Sample Efficiency

Figure 6 illustrates the sample efficiency of various alignment methods on both Arabic and English, using 10–100 training samples from the ARABPREF +CARE dataset for SFT and DPO, and 10–100 samples for DITTO. All methods outperform the baseline, with SFT and DITTO showing better performance than DPO. While these methods offer efficient training with fewer samples, their performance still lags behind full-scale training for both SFT and DPO.

Figures 7 through 9 provide a comprehensive analysis of how alignment performance scales across language and tasks. Figure 7 compares the sample efficiency of SFT, DPO, and KTO between Arabic and English contexts using 10–100% of the training data, Figures 8 and 9 offer a bifurcated view of the scaling dynamics in Arabic and English, respectively.

Method	English				Arabic			
	Cultural	General	Literacy	Avg.	Cultural	General	Literacy	Avg.
Vanilla	3.41	3.58	4.07	3.69	3.89	4.08	3.98	3.98
PALM (SFT)	4.02	4.28	4.57	4.29	3.36	3.53	3.68	3.52
CARE (DPO)	4.28	**4.55**	4.06	4.30	**4.21**	**4.46**	3.66	**4.11**
CARE (KTO)	4.11	4.37	4.00	4.16	4.19	4.44	3.57	4.07
ARABPREF $_{\text{sampled}}$ (DPO)	4.02	4.26	4.33	4.20	3.87	4.14	4.09	4.03
ARABPREF $_{\text{sampled}}$ (KTO)	3.87	4.31	**4.65**	4.28	3.54	3.98	4.13	3.88
ARABPREF $_{\text{sampled}}$+CARE (DPO)	**4.50**	4.32	4.37	**4.40**	4.01	3.87	4.01	3.96
ARABPREF $_{\text{sampled}}$+CARE (KTO)	4.08	4.14	4.26	4.16	3.67	3.96	**4.14**	3.92
ARABPREF $_{\text{sampled}}$+CARE (SFT)	4.17	4.35	4.23	4.25	3.76	4.23	4.05	4.01

Table 12: Scale-controlled sampled-data ablation on Qwen-2.5-7B-Instruct. We construct ARABPREF $_{\text{sampled}}$ by sampling 30 preference pairs per country across diverse aspects, in order to reduce the data-volume advantage of combining ARABPREF with CARE. Under this controlled setting, ARABPREF $_{\text{sampled}}$+CARE with DPO achieves the best English Cultural score and English average score, outperforming the CARE-only DPO baseline. This indicates that ARABPREF contributes complementary cultural preference signals beyond merely increasing the amount of training data.

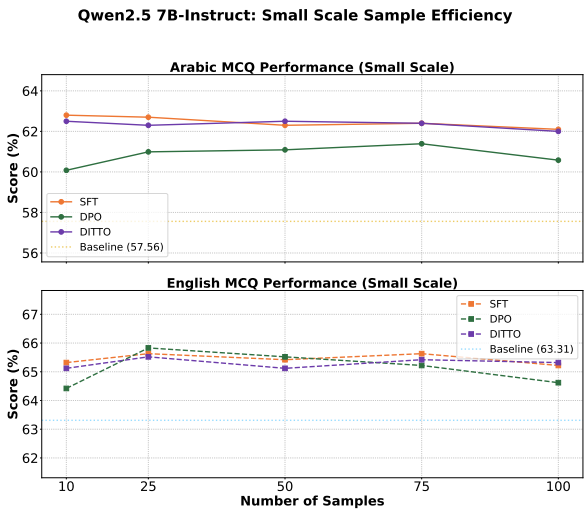

Figure 6: Sample efficiency of preference data alignment on Qwen2.5-7B-Instruct and evaluate on MCQs. Qwen2.5-7B-Instruct performance with SFT, DPO, and DITTO (10–100 samples). Dotted lines indicate zero-shot baselines

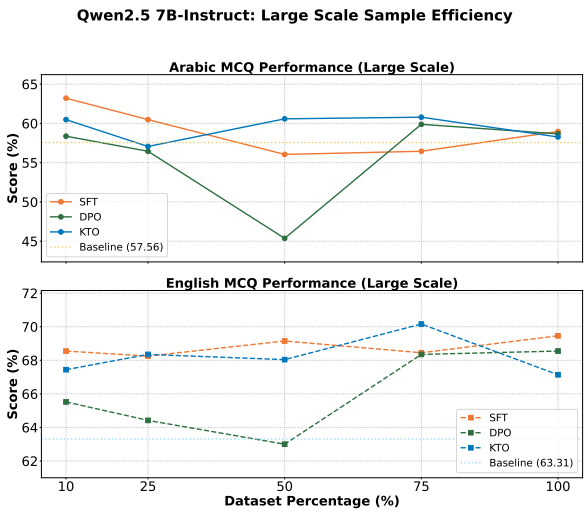

Figure 7: Sample efficiency of alignment methods on Arabic and English cultural preference MCQ evaluation. Qwen2.5-7B-Instruct performance across SFT, DPO, and KTO with 10–100% of training data. Baselines (dotted) show zero-shot performance.

To test whether combining ARABPREF and CARE helps only through scale, we conduct a sampled-data ablation with Qwen-2.5-7B-Instruct. Specifically, we construct ARABPREF $_{\text{sampled}}$ by sampling 30 preference pairs per country across diverse cultural aspects, yielding a substantially smaller and controlled subset of ARABPREF. We then evaluate models trained with ARABPREF $_{\text{sampled}}$, CARE, and their combination under the same generative evaluation protocol.

As shown in Table 12, ARABPREF $_{\text{sampled}}$+CARE with DPO achieves the highest English Cultural score and English average score, outperforming the CARE-only DPO baseline despite the controlled data setting.

This suggests that the improvement is not simply a consequence of adding more training instances; rather, ARABPREF provides complementary cultural preference signals that improve cross-lingual cultural alignment, particularly in English evaluation. At the same time, CARE-only DPO remains strongest on the Arabic average score, indicating that the two resources contribute different and complementary alignment signals.

F Correlation Coefficiency

Correlation in data annotation We sample 100 preferences from English and Arabic, with 20 sam-

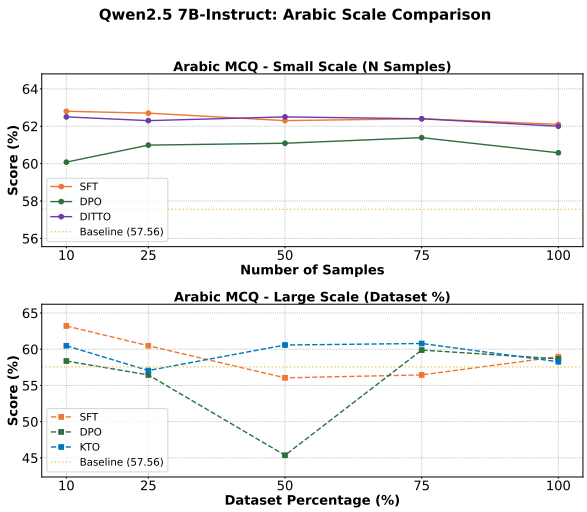

Figure 8: Scale comparison of alignment methods on Arabic cultural preference MCQ evaluation. Qwen2.5-7B-Instruct performance in small-scale (top; 10–100 samples with SFT, DPO, DITTO) and large-scale (bottom; 10–100% data with SFT, DPO, KTO) settings. Baselines (dotted) show zero-shot performance.

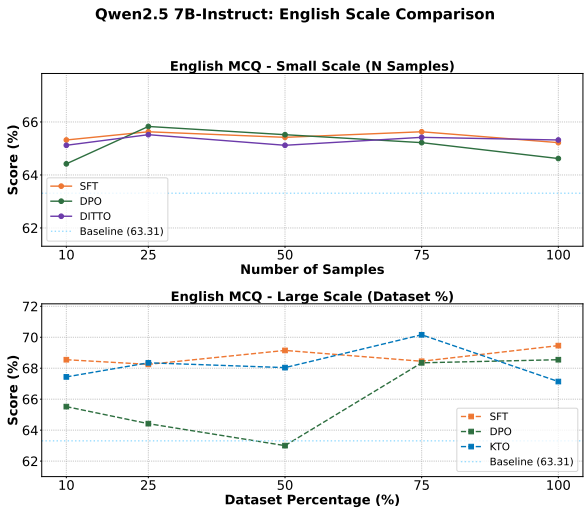

Figure 9: Scale comparison of alignment methods on English cultural preference MCQ evaluation. Qwen2.5-7B-Instruct performance in small-scale (top; 10–100 samples with SFT, DPO, DITTO) and large-scale (bottom; 10–100% data with SFT, DPO, KTO) settings. Baselines (dotted) show zero-shot performance.

ρ	Cultural	General	Literacy
En	0.7140	0.8312	0.8950
Ar	0.6707	0.7801	0.7398

Table 13: Spearman's ρ values for different categories (Cultural, General, Literacy) for both English (En) and Arabic (Ar).

ples from each of the following countries: Egypt, Syria, Morocco, UAE, and Tunisia. Human annotators, all of whom are native Arabic speakers from these countries, are asked to score the samples based on cultural appropriateness, general quality, and literacy. Annotators are provided with the evaluation guidelines outlined in Appendix C to ensure consistency. The current available results are presented in Table 13. Both Arabic and English demonstrated high correlation between the machine scoring and human scoring based on the Spearman's ρ values.

G Stability of LLM-as-a-Judge Evaluation

To assess the stability of our LLM-as-a-judge evaluation, we conducted a repeated-scoring audit using 100 country-stratified prompts, comprising 50 English and 50 Arabic prompts. We evaluated two model configurations per prompt, yielding 200 responses.

Each response was scored on three dimensions, Cultural Appropriateness, General Quality, and Literacy, yielding 600 response, rubric units per repetition. We repeated the evaluation three times using the same judge configuration, resulting in 1,800 independent scoring calls. We measured agreement across the three repetitions using Fleiss' κ, treating the 1–5 Likert ratings as categorical judgments. The resulting Fleiss' κ was 0.9503, indicating near-perfect agreement across repeated evaluations. This high agreement suggests that the reported results are not substantially affected by stochastic variation in the judge outputs under our evaluation configuration. It also supports the reliability of the judge-based evaluation for comparing model performance across the three dimensions.

H Prompts for Generation and Evaluation

In this section, we provide the exact prompts used for evaluation. Placeholders are typeset in monospace and replaced with the corresponding example fields at inference time. Whitespace, field names, output formats, and parser rules are versioned together with these prompts. For better reproducibility, we recommend using the temperature and sampling settings indicated earlier in the paper and the official provider APIs. We preserve the system and user message structure used in each experiment. Model outputs are parsed according

to the specified format without manual correction. The prompts include explicit task definitions, evaluation criteria, and output requirements to ensure consistent interpretation across models. We also retain the original ordering of instructions and input fields, as changes to prompt structure may affect model behavior and evaluation outcomes.

H.1 MCQ Rewriting

Prompt 1 rewrites MCQ options to create plausible and culturally grounded distractors while preserving the correct answer. It also standardizes the question language and returns the revised example as JSON. The prompt removes explicit country references and subjective interpretations to ensure that each option describes behavior in neutral terms.

Prompt 1: MCQ Rewriting Prompt

You are given a JSON object describing a cultural behavior question comparing two or more locations. Revise the four options (opa, opb, opc, opd) to make them more distractive while keeping the correct answer unchanged.

Rules:

1) Correct any grammatical errors in the question.
2) Unless necessary, keep the correct answer's option text unchanged.
3) Among the three distractors:
   - One must describe the opposite behavior of the correct answer.
   - The other two distractors should reflect realistic norms or values from the distractor country (or countries) listed in `distractor_country`, given the aspect; if possible, make them different from the correct answer's action.
   - You may modify the distractors, but do not change their positivity.
4) Ensure all options sound plausible and culturally grounded.
5) Avoid explicitly mentioning any country names in the options; use anonymous descriptions.
6) If the original text includes comment adjectives (e.g., "progressive," "modern," or "traditional"), rephrase them using neutral language.
7) If the original text includes an interpretation of behavior (e.g., "regarded as disrespectful" or "it is acceptable"), remove the interpretation and describe only the behavior.
8) Return **only** the final modified JSON in the same structure as the input.

H.2 MCQ Answering

Prompt 2 presents the model with a question and four answer options. It instructs the model to select the most appropriate answer and return only its corresponding letter. This restricted output format enables consistent parsing and evaluation across models. By excluding explanations, the prompt reduces variation in response structure and supports exact-match scoring. The same instruction format is applied consistently to all four-choice examples in the evaluation set.

Prompt 2: MCQ Answering Prompt

Question: `{question}`

Options:

A. `{option_a}`
B. `{option_b}`
C. `{option_c}`
D. `{option_d}`

Please choose the most appropriate answer by returning only the letter (A, B, C, or D). Only return the letter.

H.3 Three-Choice MCQ Answering

Prompt 3 presents the model with a question and three answer options. It requires the model to select the most appropriate answer and return only its corresponding letter. This format is used for examples containing three candidate answers while maintaining consistent output parsing.

Prompt 3: MCQ Answering Prompt (3-choices)

Question: `{question}`

Options:

A. `{option_a}`
B. `{option_b}`
C. `{option_c}`

Please choose the most appropriate answer by returning only the letter (A, B or C). Only return the letter.

H.4 Pairwise Win-Rate Evaluation

Prompt 4 compares two responses to the same culturally situated question using a reference answer. It prioritizes cultural appropriateness, followed by general quality and literacy, while discouraging position and length biases. The restricted output identifies the preferred response or a tie for consistent win-rate computation.

Prompt 4: Pairwise Win-Rate Evaluation Prompt

You are an impartial evaluator comparing two responses to the same culturally situated question.

Evaluate in this priority order:
1. Cultural appropriateness for the specified country and scenario, using the reference answer as guidance.
2. General quality: factual accuracy, relevance, and sufficient coverage.
3. Literacy: fluency, grammar, and clarity in the language of the question.

Do not prefer a response because it is listed first or because it is longer. Return a tie only when neither response has a clear overall advantage under the criteria above.

Country: `{country}`
Question: `{question}`
Reference Answer: `{reference_answer}`

Response 1: `{response_1}`
Response 2: `{response_2}`

Return exactly one character: 1 if Response 1 is better, 2 if Response 2 is better, or 0 for a tie.

H.5 Cultural Appropriateness Evaluation

Prompt 5 evaluates whether a response aligns with the target country's cultural norms and values. It considers cultural sensitivity, appropriateness, and the authenticity of cultural nuance relative to the reference answer. The judge assigns a rating from 1 to 5 using the defined rubric. The country and question context are provided to ground the assessment in the intended cultural setting rather than general conventions.

Prompt 5: Criterion: Cultural Appropriateness

Please serve as an unbiased evaluator and assess the assistant response only for **Cultural Appropriateness**: alignment with the target country's cultural norms and values, sensitivity to offensive or inappropriate references, and authenticity of cultural nuance.

Use this scale:
- **1** — Completely misaligned or highly inappropriate.
- **2** — Major cultural misunderstandings or insensitive references.
- **3** — Noticeable cultural inconsistencies, but the main meaning is clear.
- **4** — Mostly aligned, with only minor cultural inaccuracies.
- **5** — Fully aligned with the supplied cultural reference.

Country: `{country}`
Question: `{question}`
Reference Answer: `{reference_answer}`
Assistant's Response: `{response}`

Return exactly: `Rating: [[number]]`

H.6 Literacy Evaluation

Prompt 6 evaluates the linguistic quality of a response in the language of the question. It considers fluency, grammar, spelling, clarity, and natural flow without assessing response content. The judge assigns a rating from 1 to 5 using the defined rubric.

Prompt 6: Criterion: Literacy

Please serve as an unbiased evaluator and assess the assistant response only for **Literacy** in the language of the question: fluency, grammar and spelling, clarity, and natural linguistic flow.

Use this scale:
- **1** — Very poor fluency; errors make the response unreadable or incoherent.
- **2** — Multiple errors substantially hinder readability.
- **3** — Noticeable errors, but the response remains understandable.
- **4** — Fluent and clear, with only minor errors.
- **5** — Fully fluent, natural, and free of material language errors.

Question language: `{language}`
Question: `{question}`
Assistant's Response: `{response}`

Return exactly: `Rating: [[number]]`

H.7 General Quality Evaluation

Prompt 7 evaluates the overall quality of a response based on factual accuracy, depth, completeness, and relevance. It uses the reference answer as guidance while allowing alternative correct formulations. The judge assigns a rating from 1 to 5 using the defined rubric.

Prompt 7: Criterion: General Quality

Please serve as an unbiased evaluator and assess the assistant response only for **General Quality**: factual accuracy, depth and completeness, and relevance to the question. Use the reference answer as guidance, while allowing other correct formulations.

Use this scale:
- **1** — Highly inaccurate, unusable, or irrelevant.
- **2** — Partially accurate but missing major information or containing major errors.
- **3** — Mostly addresses the question with adequate detail and some omissions.
- **4** — Accurate and relevant, with only minor omissions.
- **5** — Fully accurate, relevant, and sufficiently complete.

Country: `{country}`
Question: `{question}`
Reference Answer: `{reference_answer}`
Assistant's Response: `{response}`

Return exactly: `Rating: [[number]]`

I Annotation Guidelines

The annotation guidelines for cultural preference quality checking, including the review of preference-test instances, and for MSA verification are provided in Figures 10–12. The guidelines for answering and verifying the MCQ benchmark are provided in Figures 13–15.

J AI Assistant Use

In producing this work, we used Grammarly for minor grammar, spelling, and stylistic corrections. We also used ChatGPT and Claude Code to assist with LaTeX table and figure formatting, code troubleshooting, and resolving issues related to Matplotlib visualizations. All suggestions generated by these tools were carefully reviewed and verified by the authors before being incorporated into the paper. All methodological decisions, analyses, findings, interpretations, and conclusions were developed by the authors, who retain full responsibility for the final manuscript.

- Is the “Discouraged Behavior” really a behavior that locals avoid or frown upon under this aspect?

If the suggestion is **accurate**, the annotator accepts it.
If it is **inaccurate or misleading**, the annotator should reject it.

Pipeline Process

Stage 1 & 2: Cultural Preference Quality Check and MSA verification

Stage 1: Cultural Preference Quality Check

File Name Structure: stage1&2_country

File Structure (Columns to Fill):

…	Aspect	Prompt	Preferred behavior	Discouraged Behavior	Quality Check	…
…	[Behavior Aspect]	[Prompt]	[Preferred Behavior]	[Discouraged Behavior]	[Your quality check]	…

Sections to fill

country	category	aspect	prompt	preferred_behavior	discouraged_behavior	quality_check
Algeria	Safety	Lost and Found	I lost my wallet in a taxi in Algiers, what should I do?	You should report the lost wallet to the police. Taxis in Algeria usually have a system for lost items, and the police can help you trace it.	Just forget about it, it's gone. Don't bother reporting it.	

Figure 1. working document overview

Cultural Preference Quality Check

When you receive the file, in the cultural preference overview, the annotators are required to perform the following checks:

- **Understand the social aspect** in the "aspect” column
- **Assess the classification of *Preferred Behaviors* and *Discouraged Behaviors in the “Quality Check” column*** to verify whether each behavior is appropriately assigned according to the cultural norms of the social aspect. You are required to

Figure 10: Annotation for stage 1 (Cultural Preference Quality Check) and stage 2 (Cultural Preference MSA Verification), for creating preference data of ARABPREF. (Page 1)

assign behavior “Accept” and “Reject”

a. Assign “Accept” if the behaviors are culturally appropriate for the aspect and correctly classified as “Preferred” or “Discouraged.”
b. Assign “Reject” if the behavior is irrelevant, incorrectly classified, or does not genuinely reflect a preferred or discouraged practice, or is neutral.

Cultural Preference Review guidelines ***(Red highlights denote critical importance.)***

- If you are not from the region or country specified in the file title, do not work on that specific file!
- The annotators should respond based on his/her life experience in the specified country; using assistance from GPT is not allowed.
- The annotator should have a good understanding of English.

Example:

Region: Egypt
Category: Social Etiquette
Aspect: Gifts

Prompt: I want to visit a family in Egypt. What should I do regarding bringing gifts?

Preferred Behavior:
Bring a small gift when invited to an Egyptian home (e.g., pastries, fruit). Gifts are generally appreciated as a token of appreciation.

Discouraged Behavior:
Arriving empty-handed when invited to a home, giving extravagant or inappropriate gifts.

Quality Check: Accept

Stage 2: MSA Verification

Note: Do this only after you have finished stage 1.

File Name Structure: Country_# (same as in part 1)

File Structure (Columns to Fill):

…	Prompt_ar	Preferred behavior_ar	Discouraged Behavior_ar	msa_quality_check

Figure 11: Annotation for stage 1 (Cultural Preference Quality Check) and stage 2 (Cultural Preference MSA Verification), for creating preference data of ARABPREF. (Page 2)

…	[Prompt]	[Preferred Behavior]	[Discouraged Behavior]	[Your Quality Check

Sections to fill

prompt_ar	preferred_behavior_ar	discouraged_behavior_ar	msa_quality_check
	يجب عليك الإبلاغ عن المطرة. ع حفظة المفقودة للشرطة. ا تارات سيكون لدى ام ًقدا للمظاهر الجزائية في قرة الجرة ويمكن للشرطة مفقودات، ساعدتك في تعقبها.		

MSA Translation Verification

When you receive the file, the annotators are required to perform the following checks:

- **Only check the MSA prompt/preferred/discouraged triples you accepted in stage 1.**
- **Read the prompt** in the "prompt" column.
- **Review the "MSA prompt", "MSA preferred", and "MSA_discouraged" columns and provide your quality check in "msa_quality_check" column**
- **Verify the quality of the MSA translations, mark "Accept" if the translation is correct, otherwise mark "Reject"**

MSA Verification Guidelines: ***(Red highlights denote critical importance.)***

- The annotator should have a good understanding of MSA and English, and should complete the revision in MSA.
- **Grammar and Spelling:** Verify the linguistic accuracy of the text.
- **Cultural Relevance:** Assess the appropriateness of the content within the specified cultural context.

Figure 12: Annotation for stage 1 (Cultural Preference Quality Check) and stage 2 (Cultural Preference MSA Verification), for creating preference data of ARABPREF. (Page 3)

Stage 3 & 4: MCQ answering and MSA verification

Stage 3: MCQ answering

File Name Structure: stage3_Country

File Structure:

Question	Choice A	Choice B	Choice C	Choice D	Best_ Answer	Secondary_ Answer(s)
[Cultural MCQ]	[Choice A]	[Choice B]	[Choice C]	[Choice D]	[Answer given]	[Answer given]

Sections to fill:

B	C	D	E	F	G	H	I
aspect	question	opa	opb	opc	opd	best_answer	secondary_answer (optional)
Leaving a Gathering	A tourist from Lebanon is visiting Algeria. How should the visitor behave regarding Leaving a Gathering to show cultural awareness?	Express profound gratitude to the hosts for their exceptional generosity and extend personal farewells to each individual present, affirming good wishes and a desire for future encounters.	Anticipate remaining for a considerable duration after a meal or social occasion, as guests typically linger for several hours into the afternoon or late into the evening.	Engage in concise, direct farewells with the immediate hosting family members, without necessarily seeking out every other guest to bid them goodbye.	Await a collective cue or an explicit invitation from the host to depart, often leaving in a group with other attendees, rather than initiating an individual departure process.		
Urban/Rural Dialect	A film crew from France shot s	Acknowledging that Algerian Ara	Recognizing that while standard A	Insisting solely on formal Arabic or	Observing how individuals frequently blend Arabic with phrases from French or En		

MCQ Quality Check

When you receive the file for the MCQ quality check, the annotators are required to perform the following checks:

- **Understand the question** in the "question" column
- **Read the choices and answer carefully** in the "Choices A, B, C, D" and "Answer" column.
- **Choose your answer based on your own cultural background.** Please always try to choose only one answer! Always choose the **most preferred/discouraged culturally related** answer. Then mark it in the Best_Answer column.
- **If other answers are also acceptable, please mark them in the "Secondary_Answer(s)" column.** You can choose other multiple answers here. Make sure that they are also culturally related.
- **If there are no correct answers, mark "No Correct Answer" in the "Best_Answer" column** (happens very rarely :)

MCQ Quality Check Guidelines: ****(Red highlights denote critical importance.)***

- If you are not from the region or country specified in the file title, do not work on that specific file!
- The annotators should respond based on his/her life experience in the specified

Figure 13: Annotation for stage 3 (MCQ answering) and stage 4 (MCQ verification), for creating MCQ data of ARABPREF. (Page 1)

country; using assistance from GPT is not allowed.

- **Note that you are required to fill in one answer to the "Best_Answer" column; filling in the "Secondary_Answer(s)" column is optional**. In case you are uncertain about deciding among multiple answers. Always choose the best answer that is culturally related to your experience and feeling.

Stage 4: MCQ MSA Translation Verification

Note: Do this only after you have finished stage 3. Contact us before you proceed to stage 4. We will analyse the data from stage 3 and keep only questions with the agreement of the answer(s) with our data.

After completing the MCQ overview, this task requires native speakers to validate the MSA translations for selected MCQs. For each entry, they are given:

- **A question and four choices in English**
- **MSA translation from LLMs.**

English MCQ	Which of the following behaviors is the most preferred in Morocco for language use? A. Arabic is the official language. Learning a few basic Arabic phrases is appreciated. English is understood in tourist areas and among educated people. Avoid using slang or overly casual language in formal settings. B. Darija (Moroccan Arabic) is the most widely spoken language, followed by Berber languages. French is widely used in business and government. English is increasingly common in tourist areas. Learning a few basic Darija phrases is appreciated. C. Using formal Arabic (Modern Standard Arabic) in official settings; using local Jordanian dialect in informal settings; learning a few Arabic phrases is appreciated. Be mindful of religious phrases like "Inshallah" (God willing) and "Alhamdulillah" (Praise be to God). D. While Arabic is the official language, many Syrians involved in tourism or business may speak English. Learning a few basic Arabic phrases is appreciated. Avoid using offensive language or discussing sensitive political or religious topics.
MSA translation	ما هو الـ لوك المفـ ل لا تخـ ام اللـ ة ي المـ رب من بيـ الخيا ات التـلي ؟ A فـ المناطق ا سياحي وبين المتعلمين تجنب ا تخدام الـغة لعامـ ة أو غير الـر مية بشكل مفرط ـي لأماكن ا رسمية . اللغـ العربيـ هـ اللـ ة الـ سمية. و ن ا مسـ حسن تعـ بعض لعبارات العر ية الأساسية ثـ م اللغة لإنجليزيـ B والـ كومة وتـ داد شيـ ع اللغة لإنجليزية في المناطـ السيـحية. ومن لمستحسـ تعلم بعـ العبارات الأساسية الدارجة بية المغـ بية هي للغة الأكـ ر ا تشارا، تـيها اللـ ات الأمازيغية. الفرد ية تـ تخدم عـى نطاق وا ع في قطـ عي الأ ما الـ رجة (العـ . C ؛ ومن الـ ستحـ ن تعلم عض العبارا العربية كن حذ ا عند ا تخدام الـ بارات ا ديـ ية مثل "إن شاء الله" و"لحمد لله" . استخـ ام الـغة لعر ية لفصحى فـ الأماكن لرسمية؛ واسـ خدام لـ جة الأردنـ ة المحلي في الأما ن غير الـ سميـ D لم بعض العـ ار ت العربـ ة لأساسية. جنب استخـ ام الألفاظ الـ سيئ أو مناقـ ة المـ اضـ ع السيا ية أو الـ ينـ ة الحـ اسة اللغة الـ سمية، إ أن العـ يد من ا سوريـ ن العامليـ في السـ احة أو ا عما قد تحدثون ا نجلـ زية. ومن الـ ستحسن تـ عـ الرغم ن ن اللغة لعربية هـ .

The native speaker should review the question and verify the MSA translation.

Figure 14: Annotation for stage 3 (MCQ answering) and stage 4 (MCQ verification), for creating MCQ data of ARABPREF. (Page 2)

File Name Structure: stage4_Country_#

File Structure (Column to fill):

English MCQ	MSA MCQ	Revision
[English MCQ]	[MSA MCQ]	[Your Revision]

Sections to fill:

aspect	English MCQ	Arabic MCQ	Revision
Shoes in Home	Q: You are a foreign employee working in Bahrain. To maintain harmony, what approach toward Shoes in Homes should you take? A. Remove your shoes before entering a home, especially if the host has done so; place soles of shoes together when removed to avoid pointing them at anyone B. Always remove your footwear when entering a Bahraini home unless explicitly told otherwise by the host; ensure your socks are presentable. C. Wearing shoes indoors without permission; showing the soles of your feet. D. Remove your shoes before entering a home or a majlis (traditional seating area).	[illegible]	

MCQ MSA Translation Check

When you receive the file for the MCQ MSA Translation quality check, the annotators are required to perform the following checks:

- **Read the English question and English choices** in the "English MCQ" column.
- **Review the Arabic MCQ** in the "Arabic MCQ" column.
- **Verify the quality of the MSA translations, and** provide your own MSA revision of the whole MCQ.

MCQ MSA Translation Guidelines: ***(Red highlights denote critical importance.)***

- The annotator should have a good understanding of Arabic and English, and should complete the revision in MSA.
- The annotator should ensure the revised MSA translation is correct.

Figure 15: Annotation for stage 3 (MCQ answering) and stage 4 (MCQ verification), for creating MCQ data of ARABPREF. (Page 3)