

Beyond MCQ: An Open-Ended Arabic Cultural QA Benchmark with Dialect Variants

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Abstract

Large Language Models (LLMs) are increasingly used to answer everyday questions, yet their performance on culturally grounded and dialectal content remains uneven across languages. We propose a comprehensive method that (i) translates Modern Standard Arabic (MSA) multiple-choice questions (MCQs) into English and several Arabic dialects, (ii) converts them into open-ended questions (OEQs), (iii) benchmarks a range of zero-shot and fine-tuned LLMs under both MCQ and OEQ settings, and (iv) generates chain-of-thought (CoT) rationales to fine-tune models for step-by-step reasoning. Using this method, we extend an existing dataset in which QAs are parallelly aligned across multiple language varieties, making it, to our knowledge, the first of its kind. We conduct extensive experiments with both open and closed models. Our findings show that (i) models underperform on Arabic dialects, revealing persistent gaps in culturally grounded and dialect-specific knowledge; (ii) Arabic-centric models perform well on MCQs but struggle with OEQs; and (iii) CoT improves judged correctness while yielding mixed n-gram-based metrics. The developed dataset will be publicly released to support further research on culturally and linguistically inclusive evaluation.

Keywords: Cultural Knowledge; Everyday Knowledge, Open-Ended Question, Chain-of-Thought

1. Introduction

Cultural information underpins human identity, behavior, and social interaction, encompassing shared beliefs, values, customs, languages, traditions, and collective practices. In today's tightly coupled information-communication ecosystem, hundreds of millions of users interact with LLMs for everyday queries, often asking about local norms, holidays, cuisine, or etiquette, where culturally grounded interpretations are essential (Pawar et al., 2025; Hasan et al., 2025). Yet despite rapid progress in multilingual understanding and reasoning, LLM performance remains uneven across languages, dialects, and culturally specific domains (Wei et al., 2022; Muenninghoff et al., 2023). The issue is especially salient for Arabic, where Modern Standard Arabic (MSA) coexists with numerous regional dialects that differ in phonology, morphology, lexicon, and usage (Alwajih et al., 2025a; Sadallah et al., 2025). Beyond modeling challenges, widely used multiple-choice (MCQ) evaluations can mask deficiencies in reasoning by enabling

MCQ	OEQ
في أي عام حصلت الكويت على أول ميدالية أولمبية؟	في أي عام حصلت الكويت على أول ميدالية أولمبية؟
Translation: <i>In what year did Kuwait win its first Olympic medal?</i>	Translation: <i>In what year did Kuwait win its first Olympic medal?</i>
Options: (A) 1996 (B) 2004 (C) 1984 (D) 2000	Answer: 2000
CoT for OEQ	
السؤال معلومي (غير رأي)، تاريخياً تُعد أول ميدالية أولمبية الكويت هي برونزية الرماية (البقر/التراپ) التي تلتها فهد الدجاني في أولمبياد سيدني، مما يحدد السنة بدقة إلى 2000	
Translation: The question is factual. Historically, Kuwait's first Olympic medal was the bronze in shooting (trap) won by Fehaid Al-Deehani at the Sydney Olympics, which pinpoints the year as 2000	
Language varieties: Modern Standard Arabic (MSA,), English (, Levantine ()), Gulf (), Egyptian (, Maghrebi ())	

Figure 1: Example QA shown in two formats (MCQ and OEQ). MCQ: Multiple-Choice Question; OEQ: Open-Ended Question. Flags in parentheses indicate representative countries where each dialect is widely spoken.

shortcut strategies such as label bias or option-guessing, complicating fair cross-lingual and cross-format comparison (Raman et al., 2025; Li et al., 2024b). A central open problem is how to *measure* and *improve* an LLM's ability to understand and generate responses to such culturally embedded queries, especially in multilingual settings with substantial dialectal variation. Another noteworthy aspect is that multiple-choice questions (MCQs) have long

been the dominant format for evaluating QA performance in large language models (LLMs) due to their simplicity, automatic scoring, and structured answer space (Myrzakhan et al., 2024). However, models can sometimes exploit the test format rather than genuinely understanding the question, leading to a form of selection bias, for instance, consistently favoring certain options (e.g., always choosing “A”) regardless of content.

To address these challenges, parallel efforts have emerged to develop culturally aligned language models (Wang et al., 2023) and to enable their efficient deployment in low-compute environments (Hu et al., 2022). At the same time, new culturally relevant datasets, targeted benchmarks, and evaluation protocols are beginning to operationalize the measurement of everyday cultural knowledge (Myung et al., 2024; Li et al., 2024a; Mousi et al., 2025; Alam et al., 2025). Collectively, these trends demonstrate the need for new resources, evaluations, and models that are grounded in underrepresented dialectal varieties and culturally contextualized content.

To shade a light on the challenges, we introduce a comprehensive method for developing a new resource for under-representative language verities. Starting from an existing MSA MCQ dataset (Alwajih et al., 2025b), we perform the following steps: (i) translate the questions into several Arabic dialects and English, (ii) convert the MCQs into open-ended questions (OEQ) that require free-form answers, (iii) evaluate a range of zero-shot and fine-tuned LLMs on the resulting benchmark, and (iv) create and fine-tune models on chain-of-thought (CoT) annotations to encourage explicit reasoning for OEQ. An example of MCQ, OEQ with CoT is shown in Figure 1.

Our approach allows us to isolate and study the impact of question format, language variety, and reasoning supervision on model performance. We find that OEQ settings present greater challenges than MCQ, especially in dialectal Arabic. Our contributions are as follows:

- We construct a multilingual and multidialectal QA dataset by translating MSA MCQs into English and multiple Arabic dialects.

- We convert the dataset to OEQs in all language variants, enabling more rigorous evaluation of model knowledge.
- We benchmark a range of zero-shot and fine-tuned LLMs under both MCQ and OEQ settings.
- We generate chain-of-thought (CoT) annotations for OEQ and fine-tune models.

This work represents the first effort to unify dialectal Arabic QA, open-ended reasoning, and CoT fine-tuning in a single benchmark, offering new insights into LLM performance on culturally rich, linguistically diverse data.

2. Related Work

General Capabilities of LLMs. Large language models (LLMs) have demonstrated impressive general capabilities across a variety of NLP tasks, including text generation, translation, summarization, and reasoning (Abdelali et al., 2024). At sufficient scale, LLMs exhibit *emergent abilities*, such as multi-step inference and commonsense reasoning (Bubeck et al., 2023; Wei et al., 2022). Prompting techniques like few-shot and chain-of-thought (CoT) significantly enhance performance on reasoning-heavy tasks (Kojima et al., 2022; Wei et al., 2022). However, most evaluations focus on English or high-resource languages. Performance often degrades on morphologically rich or low-resource languages such as Arabic, particularly in dialectal contexts (Mousi et al., 2025; Muennighoff et al., 2023).

Cultural and Everyday Knowledge. Recent research has highlighted the limitations of LLMs in capturing culturally grounded, everyday knowledge. Myung et al. (2024) introduced BLEnD, a multilingual benchmark comprising 52.6K QA pairs across 13 languages and 16 regions, designed to evaluate models’ understanding of daily-life knowledge. Similarly, Hasan et al. (Hasan et al., 2025) developed MultiNativQA, featuring 64K QA pairs covering nine locations in seven languages. Across these studies, results consistently show that LLMs underperform on questions reflecting underrepresented cultures, often default-

ing to Western-centric norms. In the Arabic context, Sadallah et al. (2025) proposed ARAB-CULTURE, a benchmark of 3.5K MSA-based multiple-choice questions authored by native speakers from 13 Arab countries to assess culturally specific commonsense reasoning. Likewise, Alwajih et al. (2025a) introduced PALM, a dialect-rich instruction dataset encompassing all 22 Arab countries.

Challenges in Converting MCQ to OEQ.

Many evaluation benchmarks use MCQs because they allow straightforward automatic scoring, in which the model selects an option (A/B/C/D) that can be directly compared with the correct answer. However, recent studies show that this format may introduce artificial performance gains and mask a model’s actual reasoning ability (Molfese et al., 2025; Chandak et al., 2025; Myrzakhan et al., 2024). For instance, LLMs often display a *selection bias*, favoring certain options (e.g., consistently choosing “A”) due to training artifacts. To mitigate these issues, several works propose converting MCQs into OEQs that require the model to generate answers without predefined choices (Myrzakhan et al., 2024). This forces reliance on internal knowledge and reasoning rather than elimination or guessing. Yet, this conversion introduces new challenges: some MCQs become ambiguous once options are removed, and others may yield multiple valid answers unless carefully rephrased. Moreover, evaluating free-form responses is inherently harder, as correctness depends on comparing generated text with gold answers that may differ in wording. Prior work addresses this by using LLM-based evaluation pipelines (e.g., GPT-4) to judge open-ended answers against human references with high reliability (Myrzakhan et al., 2024). Overall, shifting from MCQ to open-ended formats holds promise for revealing deeper model understanding, but it demands careful question selection and robust evaluation protocols.

Chain-of-Thought (CoT) Reasoning. Chain-of-thought (CoT) prompting has emerged as a powerful technique for enhancing reasoning

capabilities in large language models (LLMs). Instead of producing an answer directly, the model is encouraged to generate an explicit, step-by-step reasoning path before reaching a final conclusion (Wei et al., 2022). By articulating these intermediate steps, models can decompose complex problems into manageable components, leading to substantial gains in accuracy. Remarkably, even without task-specific training, simply prefixing the prompt with “Let’s think step by step” can induce this behavior in sufficiently large models, a method known as *zero-shot CoT* (Qin et al., 2023). This simple prompting strategy has demonstrated significant improvements across a wide range of reasoning tasks, including mathematical problem solving and commonsense reasoning. Furthermore, Qin et al. (2023) introduced a *self-consistency* mechanism, in which the model generates multiple reasoning chains and selects the most frequent answer, further enhancing performance. While most existing studies emphasize inference-time CoT, recent research has explored *CoT fine-tuning* to transfer reasoning skills to smaller or multilingual models (Puerto et al., 2025). However, to the best of our knowledge, no prior work has applied CoT fine-tuning to Arabic open-ended QA datasets, particularly those covering dialectal varieties, which constitutes a key contribution of our study.

3. Datasets

Our data is based on the **PalmX 2025 - General Culture Evaluation (PalmX-GC)** dataset, which assesses a model’s understanding of Arab culture, including customs, history, geography, arts, cuisine, notable figures, and everyday life across the 22 Arab League countries. All questions and answers are written in MSA and manually verified, providing a robust benchmark for culturally grounded QA (Alwajih et al., 2025b). The dataset comprises 2,000 training, 500 development, and 2000 test examples, all in MCQ format. We use PalmX-GC as the foundation for creating dialectal MCQ and OEQ variants. Figure 2 illustrates the dataset construction process. In the entire pipeline,

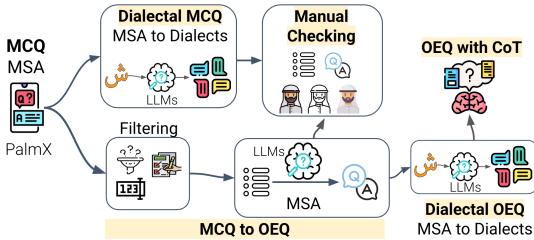


Figure 2: Pipeline for the dataset construction process.

we used LLMs (specifically GPT-4.1) for both translation and data conversion. Our choice of this model was primarily based on its reliability and our available paid access.

3.1. Dialectal MCQ

To broaden cultural and linguistic coverage beyond MSA, we translate PalmX into four Arabic dialect Egyptian, Levantine, Gulf, and Maghrebi, and into English GPT-4.1 with a quality check. These dialects were selected because (i) they collectively cover the largest speaker populations and the widest geographic spread across the Arab world; (ii) they capture major points on the Arabic dialect continuum with substantial lexical, morphological, and pragmatic divergence from MSA; and (iii) they are the primary medium of everyday communication and online discourse, where culturally grounded queries naturally occur. Including English serves two purposes: it provides a lingua-franca baseline for cross-lingual comparison (disentangling language modeling from culture-specific knowledge) and reflects real usage, where users often pose culturally focused questions in English about Arabic contexts. This design enables us to probe (a) format sensitivity ($\text{MCQ} \rightarrow \text{OEQ}$), (b) dialect sensitivity (MSA vs. regional varieties), and (c) cross-lingual transfer ($\text{Arabic} \leftrightarrow \text{English}$) within a single, controlled benchmark.

We employed controlled prompting to translate each MSA MCQ into four dialects and *English*. The prompts explicitly enforced semantic equivalence while allowing lexical and stylistic adaptation to dialectal norms. This approach ensured that the dialectal phrasing preserved

the original question’s intent without causing any semantic drift from its MSA counterpart.

3.2. MCQ to OEQ

We converted the MSA MCQs into OEQs using GPT-4.1. Each MCQ was transformed into a natural question–answer pair by rephrasing the original question and its correct option into a single, self-contained QA instance. The remaining distractors were used only to guide contextual understanding but were excluded from the final prompt. We filtered out QA items where conversion was structurally infeasible, such as questions dependent on visible alternatives, to avoid ill-posed or underspecified open-ended forms. This process ensured that the resulting OEQs were faithful derivations of verified MCQs rather than arbitrary generations.

3.3. Dialectal OEQ

We then translated the OEQs into dialectal variants using similar controlled prompting principles, promoting authentic dialectal translation while preserving both semantic and pragmatic fidelity to the original MSA version. The resulting dataset constitutes a parallel corpus spanning five dialects and English, each aligned with consistent cultural grounding and verified equivalence. This parallel structure enables systematic evaluation of dialectal reasoning and transfer capabilities in generative settings.

3.4. OEQ with CoT

Inspired by prior work (Yu et al., 2025; Zelikman et al., 2022), we transform each OEQ instance $x = (q, a^*) \in \text{dataset } D$, where q denotes the question and a^* the gold or reference answer, into one or more CoT training samples using a four-stage pipeline. The pipeline generates multiple reasoning chains without revealing the gold answer, optionally produces gold-conditioned rationalizations, and verifies accepted chains. While generating CoTs, we also prompt the LLM to classify each q as either *factual* or *subjective*. Identifying the question type enables type-specific model development

and evaluation. For instance, factual questions may require reference evidence or source attribution for their answers.

Preliminaries. Let N = samples be the number of chain attempts, T = rationalize_target the minimum number of gold-aligned chains to retain, and ρ = accept_ratio $\in (0, 1]$ the acceptance threshold. For each attempt $i \in \{1, \dots, N\}$, we obtain $(\hat{c}_i, \hat{a}_i, \hat{\ell}_i)$, where $\hat{c}_i \in \mathcal{C}$ is a generated chain-of-thought, $\hat{a}_i \in \mathcal{Y}$ is the generated answer, and $\hat{\ell}_i \in \mathcal{L} = \{\text{factual, subjective}\}$ is a label. Let also denote the collection of attempts as $\mathcal{S} = \{(\hat{c}_i, \hat{a}_i, \hat{\ell}_i)\}_{i=1}^N$ and the accepted subset as $\mathcal{K} \subseteq \mathcal{S}$. Acceptance is determined via a matching function $\text{match} : \mathcal{Y} \times \mathcal{Y} \rightarrow \{0, 1\}$ (see MATCH) against the gold answer a^* , with indicator $m_i = \mathbb{I}\{\text{match}(\hat{a}_i, a^*) = 1\}$. We enforce $|\mathcal{K}| \geq T$ and the empirical acceptance ratio $|\mathcal{K}|/N \geq \rho$.

1. CoT generation. Let $\mathcal{G} : \mathcal{Q} \rightarrow \mathcal{C} \times \mathcal{Y} \times \mathcal{L}$ denote the rationale-answer-label generator. For each $q \in \mathcal{Q}$, we sample $(\hat{c}_i, \hat{a}_i, \hat{\ell}_i) = \mathcal{G}(q)$. For each attempt, compute the match flag $m_i = \mathbb{I}\{\text{match}(\hat{a}_i, a^*) = 1\}$ and collect the kept subset $\mathcal{K} = \{(\hat{c}_i, \hat{a}_i, \hat{\ell}_i) \in \mathcal{S} : m_i = 1\}$.

2. CoT rationalize with gold. Let $\mathcal{R} : \mathcal{Q} \times \mathcal{Y} \rightarrow \mathcal{C} \times \mathcal{Y} \times \mathcal{L}$ denote the gold-conditioned rationalizer. If $|\mathcal{K}| < T$ (as obtained in Step 1), we draw additional chains via $(\tilde{c}_j, \tilde{a}_j, \tilde{\ell}_j) = \mathcal{R}(q, a^*)$ and retain those that match the gold answer: $\tilde{m}_j = \mathbb{I}\{\text{match}(\tilde{a}_j, a^*) = 1\}$, $\tilde{\mathcal{K}} = \{(\tilde{c}_j, \tilde{a}_j, \tilde{\ell}_j) : \tilde{m}_j = 1\}$. We then update $\mathcal{K} \leftarrow \mathcal{K} \cup \tilde{\mathcal{K}}$ until $|\mathcal{K}| \geq T$ (and, if applicable, $|\mathcal{K}|/N \geq \rho$). This stage ensures a sufficient pool of gold-aligned CoT for downstream use.

3. Verification. Let $\mathcal{V} : \mathcal{Q} \times \mathcal{Y} \times \mathcal{C} \times \mathcal{Y} \rightarrow [0, 1] \times \{\text{pass, fail}\} \times \text{Report}$ denote the verifier, where the two \mathcal{Y} components correspond to the gold answer a^* and the candidate answer a_k , respectively. For each retained item $(c_k, a_k, \ell_k) \in \mathcal{K}$, compute $(\sigma_k, \nu_k, r_k) = \mathcal{V}(q, a^*, c_k, a_k)$, where $\sigma_k \in [0, 1]$ is a confidence score, $\nu_k \in \{\text{pass, fail}\}$ is the verdict under a default threshold $\tau = 0.8$ (i.e., $\nu_k = \text{pass}$ iff $\sigma_k \geq \tau$), and r_k is a brief issue report. We then form the verified subset

$\mathcal{K}_{\text{ver}} = \{(c_k, a_k, \ell_k) \in \mathcal{K} : \nu_k = \text{pass}\}$, noting that ℓ_k is carried forward but not used by \mathcal{V} .

Answer matching *match*. We follow very weak answer matching approach. Given a generated answer \hat{a} and gold a^* , define $\text{match} : \mathcal{Y} \times \mathcal{Y} \rightarrow \{0, 1\}$ by $\text{match}(\hat{a}, a^*) = 1$ iff at least one holds: (i) exact normalized equality, $\text{norm}(\hat{a}) = \text{norm}(a^*)$; (ii) high token Jaccard, $J(P, G) = \frac{|P \cap G|}{\max(1, |P \cup G|)} \geq 0.75$, where $P = \text{tokset}(\hat{a})$ and $G = \text{tokset}(a^*)$; (iii) small-set containment, $(|P| \leq 6 \wedge P \subseteq G) \vee (|G| \leq 6 \wedge G \subseteq P)$; (iv) high character similarity, $\text{sim}(\text{norm}(\hat{a}), \text{norm}(a^*)) \geq \tau$, with $\tau = 0.88$ and sim computed sequence matching algorithm¹. Otherwise, $\text{match}(\hat{a}, a^*) = 0$.

To facilitate the answer matching, we use language-aware normalization $\text{norm}(\cdot)$. For Arabic, we remove diacritics, and drop non-{Arabic letters/digits/_} characters. For non-Arabic, we apply unicode normalization, lowercase, and remove non-{a–z, 0–9} characters. We set $\text{tokset}(s) = \text{set}(\text{norm}(s) \text{ split on spaces})$.

3.5. Manual Checking

As shown in Figure 2, we conducted a targeted manual evaluation on small samples from each task (e.g., dialectal translation checks and MCQ→OEQ conversions). For each dialect, one native Arabic speaker (fluent in English) reviewed the items. Annotators participated on a voluntary basis. We acknowledge that having a single annotator per dialect is a limitation; nonetheless, this pass provided a practical, low-latency quality screen before larger-scale studies.

Our evaluation rubrics capture complementary aspects of downstream utility: (i) *Dialectal naturalness* for sociolinguistic authenticity, (ii) *Meaning preservation* for semantic fidelity, (iii) *Logical coherence* to avoid ill-posed or inconsistent items, (iv) *Question-type appropriateness* to ensure valid MCQ→OEQ conversion,

¹<https://docs.python.org/3/library/difflib.html>

and (v) *Linguistic quality and clarity* for grammaticality and readability. We use a five-point Likert scale as it provides (a) sufficient granularity to capture meaningful differences, (b) symmetric anchors with a neutral midpoint for ambiguity, and (c) easy aggregation across annotators and tasks. Each dimension is rated on $1, \dots, 5$.

Each rubric is briefly described below.

- **Dialectal naturalness:** Do the question and (if applicable) options sound authentic, fluent, and idiomatic in the target dialect?
- **Meaning preservation:** Does the OEQ/translation convey the same meaning and intent as the original MCQ/source?
- **Logical coherence:** Are the question and (if applicable) options logically consistent, factually sound, and contextually appropriate?
- **Question-type appropriateness:** Is the chosen format valid for the content (MCQs are decidable by selection; OEQs are genuinely open-ended)?
- **Linguistic quality and clarity:** Are grammar, wording, and orthography correct and easily understood by native speakers?

Table 1 summarizes the manual annotation results, with an overall average of 4.4, between mostly true and true. Maghrebi received the highest average - 4.8, while English scored lowest - 4.1. Meanwhile, for MSA MCQ to OEQ transformation performed well - 4.3, largely preserving meaning and structure.

Metric	MSA	Lv	Eg	Gf	En	Mg
Dialectal naturalness	4.2	4.4	4.3	4.3	4.2	4.7
Meaning preservation	4.6	4.6	4.3	4.3	4.0	4.7
Logical coherence	4.2	4.4	4.3	4.3	4.0	4.8
Question-type appropriateness	4.1	4.7	4.3	4.4	4.2	4.8
Linguistic quality and clarity	4.2	4.5	4.4	4.4	4.0	4.8
Average	4.3	4.5	4.3	4.4	4.1	4.8

Table 1: Average Likert score from manual annotations on a sample of 50 dialectal MCQs and MSA OEQs derived from MSA MCQs. Lv: Levantine, Eg: Egyptian, Gf: Gulf, En: English, Mg: Maghrebi.

4. Experiments

Models. For the experiments, we used a range of open and closed-source multilin-

gual and Arabic-centric models, covering capacities from small open models to frontier systems. The models include *Falcon3-10B-Instruct* (Malartic et al., 2024), *NileChat-3B* (Mekki et al., 2025), *Fanar-1-9B-Instruct* (Team et al., 2025), *Qwen2.5-3B* and *Qwen2.5-7B* (Wang et al., 2024), *GPT-4.1* and *GPT-5* (OpenAI, 2025), and *ALLaM-7B-Instruct-preview* (Bari et al., 2025). This selection covers both high-performing proprietary and open models under 10B parameters, suitable for controlled fine-tuning and reproducible evaluation.

Benchmarking. All models were evaluated in a zero-shot setting across multiple language varieties. Prior work on cross-lingual prompting (Kmainasi et al., 2025) has shown that non-native (English) prompts consistently outperform native prompts in reasoning and factual tasks, even for Arabic-centric models-while mixed prompts yield intermediate results. Following these findings, all model evaluations in this study were conducted using English prompts.

For the MCQ evaluation, a structured prompting template was designed to present the question along with its answer options. For OEQ, a separate open-ended prompting template is used to generate responses.

Training. We adopt fine-tuning configurations consistent with prior work on Arabic cultural QA tasks, as reported in (Bhatti et al., 2025). Fine-tuning is conducted over 3 epochs using LoRA adapters (Hu et al., 2022), with a maximum sequence length of 512 for MCQ training and 2048 for OEQ training. The learning rate is set to 2×10^{-4} , with a LoRA rank of 64 and $\alpha = 16$. All models are fine-tuned for MCQ evaluation, while only ALLaM-7B-Instruct-preview is fine-tuned for the OEQ task.

Evaluation and Metrics. For MCQ, we report accuracy, which is a standard metric for MCQ. For OEQ, we employ semantic evaluation using BERTSCORE (Zhang et al., 2020) and ROUGE-L (Lin, 2004) to assess precision, recall, and overall semantic overlap with the

Model	MSA	Egyptian	Levantine	Magrebi	Gulf	English	Average
Falcon3-10B-Instruct	46.05	43.95	44.10	42.70	45.15	66.50	48.48
Falcon3-10B-Instruct FT	57.65	55.15	54.25	53.60	55.95	71.90	58.17
NileChat-3B	67.55	64.75	64.65	64.45	66.00	65.15	65.00
NileChat-3B FT	69.20	67.75	67.65	66.90	67.45	69.05	67.76
Fanar-1-9B-Instruct	65.75	62.95	62.40	61.00	61.45	65.30	62.62
Fanar-1-9B-Instruct FT	72.55	69.85	70.55	69.70	70.75	72.65	70.70
Qwen2.5-3B	59.65	53.70	54.50	52.65	54.85	61.50	55.44
Qwen2.5-3B FT	63.75	62.80	62.80	62.45	62.60	69.55	64.04
Qwen2.5-7B	61.95	60.25	60.65	57.05	60.60	65.15	60.74
Qwen2.5-7B FT	67.50	65.85	65.95	63.25	66.00	71.50	66.51
ALLaM-7B-Instruct-preview	67.25	65.70	64.90	64.35	66.20	62.15	64.66
ALLaM-7B-Instruct-preview FT	71.95	70.55	69.85	69.85	70.40	67.70	69.67
Avg. Arabic-Centric	66.85	64.47	63.98	63.27	64.55	64.20	64.09
Avg. Arabic-Centric FT	71.23	69.38	69.35	68.82	69.53	69.80	69.38
Avg. Base All	61.37	58.55	58.53	57.03	59.04	64.29	59.49
Avg. FT All	67.10	65.33	65.18	64.29	65.53	70.39	66.14
GPT-4.1	77.42	79.08	78.29	80.24	79.33	78.57	79.10
GPT-5	79.59	79.10	78.88	77.70	79.31	77.17	78.43

Table 2: MCQ accuracy (%) across different language variants. Fine-tuned models (FT) are shaded in light blue, GPT models in gray, and averages for Arabic-centric models (NileChat, Fanar, ALLaM) are highlighted in light green. Bold values indicate the best-performing open model per dialect.

Model	MSA		Egyptian		Levantine		Magrebi		Gulf		English		Average	
	F1	RL												
Falcon3-10B-Instruct	0.43	0.12	0.41	0.10	0.41	0.09	0.41	0.09	0.41	0.10	0.54	0.23	0.44	0.12
NileChat-3B	0.48	0.17	0.49	0.18	0.50	0.17	0.50	0.18	0.49	0.17	0.49	0.15	0.49	0.17
Fanar-1-9B-Instruct	0.52	0.20	0.50	0.17	0.50	0.16	0.50	0.17	0.51	0.17	0.53	0.18	0.51	0.18
Qwen2.5-3B	0.45	0.13	0.43	0.11	0.43	0.10	0.44	0.11	0.44	0.11	0.47	0.11	0.44	0.11
Qwen2.5-7B	0.55	0.24	0.51	0.20	0.51	0.19	0.53	0.21	0.52	0.20	0.53	0.20	0.53	0.21
ALLaM-7B-Instruct	0.49	0.20	0.47	0.16	0.47	0.15	0.46	0.15	0.48	0.17	0.52	0.22	0.48	0.17
Avg. Arabic-Centric	0.50	0.19	0.49	0.17	0.49	0.16	0.49	0.17	0.49	0.17	0.51	0.18	0.50	0.17
Avg. Base	0.49	0.18	0.47	0.16	0.47	0.14	0.47	0.15	0.47	0.15	0.51	0.18	0.48	0.16
GPT-4.1	0.55	0.27	0.53	0.24	0.53	0.21	0.54	0.24	0.54	0.24	0.56	0.25	0.54	0.24
GPT-5	0.57	0.28	0.54	0.24	0.54	0.22	0.55	0.24	0.55	0.25	0.54	0.22	0.55	0.24

Table 3: OEQ performance across different language variants. Averages for Arabic-centric models (NileChat, Fanar, ALLaM) are highlighted in light green. GPT models are shaded in gray.

gold answers. Arabic responses are evaluated using arabert-v2 (Antoun et al., 2020), and English responses with bert-base-uncased. This setup allows direct comparability between multilingual and dialectal outputs across all evaluated models. Additionally, for OEQ, we use GPT-4.1 as LLM-as-judge following MT-Bench (Bai et al., 2024), where responses are rated on a 1 to 10 rubric (helpfulness, relevance, accuracy, faithfulness).

5. Results

We compare performance across four conditions: (i) MCQ base vs. fine-tuned, (ii) OEQ base, (iii) OEQ fine-tuned without CoT, and (iv)

OEQ fine-tuned with CoT. Tables 2, 3, and 4 present the results for the MCQ, OEQ, and OEQ (with vs. without CoT) evaluations, respectively.

Lang	Base			FT			FT with COT		
	J	F1	RL	J	F1	RL	J	F1	RL
MSA	5.50	0.49	0.20	6.02	0.76	0.56	6.12	0.70	0.48
Eg	4.93	0.47	0.16	5.90	0.71	0.46	6.10	0.66	0.41
Lv	4.95	0.47	0.15	5.93	0.70	0.45	6.13	0.66	0.40
Mg	4.80	0.46	0.15	5.88	0.70	0.45	6.08	0.65	0.39
Gf	4.97	0.48	0.17	5.94	0.70	0.45	6.14	0.66	0.41
En	4.49	0.52	0.22	5.55	0.74	0.57	5.48	0.67	0.43
Avg.	4.94	0.48	0.17	5.87	0.72	0.49	6.01	0.67	0.42

Table 4: Performance on the OEQ across ALLaM-7B base, fine-tuned (FT), and fine-tuned with CoT models. J: LLM-as-a-judge.

Performance Gap for MCQ. As presented in Table 2, the average performance among the Arabic language variants is relatively higher for MSA across open models, followed by Gulf, Egyptian, and others. The average performance for English is higher compared to Arabic across open models, mainly due to the strong performance of non-Arabic-centric models such as Falcon and Qwen. The average performance for Arabic-centric models in the base and fine-tuned (FT) settings is 64.09% and 69.38%, respectively.

The performance of closed models (i.e., GPT*) are higher than closed models in all language variants. The MCQ performance for MSA is highly comparable with the PalmX shared task results where top-system achieved an accuracy of 72.15% (Alwajih et al., 2025b).

Among the smaller open models (i.e., size 3B), in the base setting, NileChat-3B achieves the highest average accuracy of 65.43, while Fanar-1-9B-Instruct is the best-performing fine-tuned model with an accuracy of 71.01. Among the open models, the fine-tuned ALLaM-7B-Instruct performs best for Egyptian and Maghrebi, whereas Fanar-1-9B-Instruct-FT achieves the highest performance for MSA, Le, Gf, and En.

Performance Gap for OEQ. Across language variants, we observe a pattern consistent with MCQ results: the average F1 for MSA exceeds that of other Arabic dialects; however, the gap is smaller than in the MCQ setting (Table 3). Similarly, English attains higher F1 than the Arabic variants. Notably, for OEQ, the Qwen2.5-7B open model outperforms the other open models, including Arabic-centric ones.

Among all base models, GPT-5 achieves the highest overall performance ($F1 = 0.55$), followed closely by GPT-4.1 ($F1 = 0.54$). GPT-5 performs best on MSA, while GPT-4.1 shows strong results on both English and MSA.

Did CoT help for OEQ? In Table 4, we report the performance of OEQ with a comparison to the base model, fine-tuning without CoT (FT), and fine-tuning with CoT. Other than F1 and Rouge-L score, we also report LLM-as-a-judge scores. On token-overlap metrics, FT yields the strongest scores (F1/RL), whereas the CoT-

tuned model attains the highest average *LLM-as-a-judge* score. This divergence indicates that CoT improves *semantic acceptability* but reduces *lexical overlap* with the references. A manual pass over low-F1 cases shows that the CoT model frequently returns briefer answers that judges deem correct, yet they share fewer n-grams with the (often longer) gold strings, decreasing F1 and RL. Overall, CoT helps on judged correctness but not on n-gram overlap.

This pattern aligns with prior findings that CoT is not uniformly beneficial. For instance, Zhu et al. (2025) show that adding rationales can sometimes hurt performance, while Li et al. (2025) find that fine-tuning smaller models on lengthy, teacher-generated CoT traces performs no better, or worse, than training without CoT. Together with our results, these observations highlight the need to examine when CoT is advantageous, particularly regarding task type, rationale length, and model size.

6. Conclusions and Future Work

We presented a comprehensive pipeline for converting MCQ into OEQ and extended an existing MCQ dataset into OEQ across multiple language varieties, including MSA, English, and several Arabic dialects. To our knowledge, this is the first Arabic cultural OEQ resource with parallel dialectal variants alongside English, providing a foundation for culturally grounded evaluation beyond MSA. Our resource also differs from related datasets such as Palm and PalmX: in our case, QAs are *parallelly aligned* across all language variants. We benchmarked the dataset using a spectrum of open, closed, and fine-tuned models. Fine-tuned models consistently outperform their base counterparts yet still trail strong closed models; performance is generally higher for MSA than for dialects. Arabic-centric models show advantages on Arabic variants for MCQ but smaller gains on OEQ, highlighting the added difficulty of generative, culturally grounded answering. Our initial CoT results improve judged correctness but yield mixed n-gram-based scores. Future work includes broader human validation, variety-aware nor-

malization and scoring and extensions to other low-resource languages and modalities.

7. Ethics statement

We do not anticipate ethical concerns arising from this work. We build on publicly available datasets that permit research use, and we comply with their licenses and terms. For the manual annotations, contributors participated voluntarily after being fully briefed on the task and its purpose. No personal or sensitive data were collected beyond what is contained in the source datasets.

8. Limitations

Our extensions to publicly available Arabic-dialect datasets rely on LLM-assisted translation and MCQ→OEQ conversion, which may introduce modeling biases (e.g., paraphrase drift, dialectal normalization) and occasional errors. Due to limited annotation capacity, we performed manual checks on small samples rather than exhaustive human verification. A full, dialect-sensitive manual check across varieties remains future work and would substantially improve the dataset’s reliability and utility for benchmarking dialectal cultural knowledge.

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