AraHalluEval: A Fine-grained Hallucination Evaluation Framework for Arabic LLMs

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ABSTRACT

Recently, extensive research on the hallucination of the large language models (LLMs) has mainly focused on the English language. Despite the growing number of multilingual and Arabic-specific LLMs, evaluating LLMs' hallucination in the Arabic context remains relatively underexplored. The knowledge gap is particularly pressing given Arabic's widespread use across many regions and its importance in global communication and media. This paper presents the first comprehensive hallucination evaluation of Arabic and multilingual LLMs on two critical Arabic natural language generation tasks: generative question answering (GQA) and summarization. This study evaluates a total of 12 LLMs, including 4 Arabic pre-trained models, 4 multilingual models, and 4 reasoning-based models. To assess the factual consistency and faithfulness of LLMs' outputs, we developed a fine-grained hallucination evaluation framework consisting of 12 fine-grained hallucination indicators that represent the varying characteristics of each task. The results reveal that factual hallucinations are more prevalent than faithfulness errors across all models and tasks. Notably, the Arabic pre-trained model Allam consistently demonstrates lower hallucination rates than multilingual models and a comparative performance with reasoning-based models. The code is available at: Github link.

1 Introduction

The emergence of large language models (LLMs) has marked a new era in natural language processing (NLP). LLMs demonstrate exceptional competence in generating coherent and contextually relevant text in multiple languages (Chang et al., 2024). However, hallucination remains a critical issue for LLMs. Hallucination happens when LLM generates outputs that are factually inaccurate, nonsensical, or misleading (Maynez et al., 2020). This
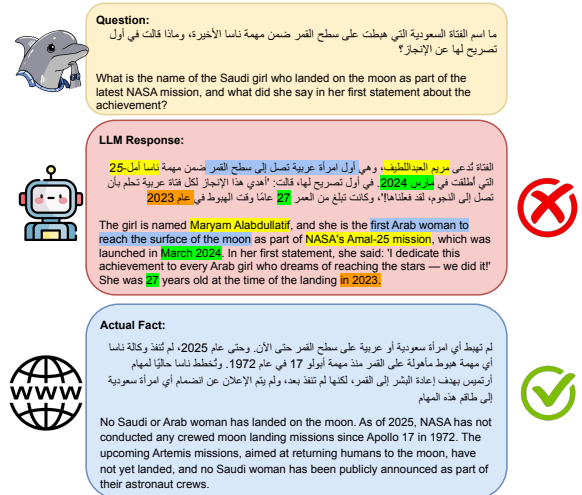

Figure 1: An example of LLM hallucination errors in the GQA task. Named-entity error denotes incorrect names of people, places, or organizations, value error denotes wrong dates, ages, or time references, factual contradiction represents information not present in the real-world, whereas response conflict represents contradicting information within the response itself.

issue not only undermines their trustworthiness but also limits their practical use in real-world applications.

Hallucination is classified into factual and faithful (Huang et al., 2025). Factuality hallucination describes the divergence between produced content and known real-world facts, often appearing as factual inconsistency or fabrication. On the other hand, faithfulness hallucination refers to the divergence from the input or context, misaligning with user instructions or internal consistency. Figure **??** illustrates an example of hallucination in Arabic Generative Question Answering (GQA). In this example, the model introduces named-entity errors (e.g., incorrect names), value errors (e.g., wrong dates), factual contradictions (e.g., claims not supported by real-world facts), and response conflicts

(e.g., internal contradictions within the generated response).

Extensive research on hallucinations in LLMs has predominantly focused on high-resource languages, such as English and Chinese (Chang et al., 2024; Huang et al., 2025). Evaluating LLMs' hallucination in the Arabic context remains relatively underexplored despite the growing number of multilingual and Arabic-specific LLMs (Bari et al., 2024; Sengupta et al., 2023). Arabic presents unique linguistic challenges due to its morphological richness, complex syntax, and diversity of dialects (Farghaly and Shaalan, 2009; Habash, 2010). These challenges make hallucination evaluation more complex and necessitate specialized benchmarks and (Mubarak et al., 2024; Abdaljalil et al., 2025)methodologies (Sibaee et al., 2024).

To address this limitation, we conduct a comprehensive evaluation of state-of-the-art (SOTA) Arabic and multilingual LLMs on two critical generative tasks: GQA and text summarization. Twelve LLMs have been evaluated in this work. We also evaluated the performance of four reasoning-based models on the TruthfulQA hallucination benchmark. Our evaluation goes beyond conventional metrics by incorporating fine-grained human evaluation to assess hallucinations using a multi-dimensional criterion encompassing both factuality and faithfulness. Twelve fine-grained hallucination types have been identified in this study and used to evaluate LLMs. Through this comparative analysis, we identify strengths and shortcomings of the evaluated LLMs in generating factual outputs. The main contributions of this study can be summarized as follows:

- Propose a multi-dimensional assessment criterion for LLMs' hallucination in Arabic.

- Evaluate hallucination in Arabic, multilingual, and reasoning-based LLMs on Arabic GQA and text Summarization tasks.

- Present a manually annotated dataset for evaluating hallucinations in Arabic LLM outputs across GQA and summarization tasks.

- Compare four reasoning-based LLMs on the TruthfulQA hallucination benchmark using parallel English and Arabic questions.

2 Related work

Hallucination in LLMs. Hallucination in LLMs compromises model reliability and poses safety concerns in real-world applications such as healthcare, education, and law. Previous studies have extensively explored hallucination in LLMs within English contexts, focusing primarily on detection and mitigation strategies (Ji et al., 2023; Chang et al., 2024; Huang et al., 2025; Rawte et al., 2023). To mitigate hallucination in LLMs, prior studies proposed strategies, such as self-verification approaches (Manakul et al., 2023b), grounding model outputs in external outputs (Lewis et al., 2020), introducing self-consistency decoding (Wang et al., 2022), and contrastive decoding (Chuang et al., 2023).

Despite the advancement in LLMs, hallucination remains understudied in low-resource languages like Arabic. While reasoning-focused models such as GPT-4o (OpenAI et al., 2024) and DeepSeek-R1 (Guo et al., 2025) show promise in mitigating hallucinations in English, their effectiveness in Arabic generative tasks is largely unknown. Meanwhile, Arabic-specific LLMs like Jais (Sengupta et al., 2023), Fanar (Team et al., 2025), and Allam (Bari et al., 2024) have been developed, but their hallucination behavior has yet to be systematically evaluated. Given Arabic's morphological complexity and dialectal variation, dedicated benchmarks are essential for evaluating factuality and faithfulness in Arabic LLM outputs (Mubarak et al., 2024). Besides, cross-lingual comparisons between Arabic-focused and multilingual LLMs—such as Gemma3 (Team et al., 2024), LLaMA3 (Grattafiori et al., 2024), and Qwen2.5 (Hui et al., 2024)—are crucial for understanding how language-specific features affect hallucination. This evaluation is crucial, as language-specific behaviors may lead to significant differences in hallucination tendencies and factual reliability when generating Arabic content.

Hallucination Evaluation. Evaluating hallucination in LLMs is essential to understand their factual reliability and ensure alignment with user intent. Accordingly, another area of research concentrates on assessing the hallucination of models across various NLP tasks. For instance, Maynez et al. (2020) provided a comprehensive study on hallucinations for abstractive summarization, revealing that SOTA models frequently generate factually and faithfully inconsistent summaries. Their study shows that even summaries with high ROUGE scores can be unfaithful, which highlights the need for better evaluation methods.

A variety of measures have been developed to

evaluate the faithfulness of abstractive summarization. The metrics encompass entailment-based measures (Kryściński et al., 2020; Goyal and Durrett, 2020; Laban et al., 2022), as well as question-generation and question-answering metrics (Fabbri et al., 2022; Manakul et al., 2023a; Subbiah et al., 2024). Recently, attention has transitioned to LLM-based metrics (Gao et al., 2023; Chan et al., 2023; Song et al., 2024) that utilize LLMs to evaluate the fidelity of a summary. To evaluate hallucination in GQA, prior research has explored multiple approaches, including fine-tuning LLMs to detect factual inconsistencies (Kadavath et al., 2022) and analyzing internal model states to identify hallucinated or factually incorrect claims (Farquhar et al., 2024; Su et al., 2024).

In parallel, several benchmark datasets have been introduced to facilitate standardized evaluation, including TruthfulQA (Lin et al., 2022), which targets common misconceptions; FreshQA (Vu et al., 2024), which focuses on time-sensitive knowledge; HaluEval (Li et al., 2023), designed for hallucination categorization. These datasets enable a more comprehensive analysis of hallucination tendencies in GQA. Despite these advancements, hallucination evaluation remains largely unexplored in the Arabic language. Most existing benchmarks and evaluation metrics have been developed for English, leaving a significant gap in assessing the factuality and faithfulness of Arabic generative outputs.

Our work bridges this research gap by providing an extensive comparative evaluation of hallucination phenomena in both Arabic-specific, multilingual, and reasoning LLMs on Arabic GQA and summarization tasks. We aim to systematically measure hallucination in LLMs, identify linguistic features contributing to hallucinations, and benchmark reasoning-enhanced models in an Arabic linguistic context.

3 AraHalluEval Framework

We evaluate the hallucination of Arabic and multilingual LLMs in a zero-shot setup on two tasks: GQA and text summarization. Figure 2 illustrates the hallucination evaluation pipeline. For each task, we fed the input data to the evaluated LLMs, and their responses were manually evaluated to determine the level of hallucination.

3.1 Tasks and Datasets

GQA. This task involves generating natural language answers to open-ended questions. The evaluated models are required to generate accurate, coherent, and contextually faithful answers. For this task, we used the Tydiqa-goldp-ar dataset (Clark et al., 2020). The TyDiQA-GoldP-AR dataset is a realistic and challenging benchmark. It aims to replicate genuine human curiosity by having annotators generate questions with minimal background knowledge of the article. We sampled 300 random questions from the test set of this dataset and fed them into the selected LLMs. Then, the output of each LLM is manually evaluated using nine hallucination indicators to measure its hallucination. We selected this number of samples because using the complete test set is challenging due to its large size and the high cost of human evaluation. Moreover, we used the TruthfulQA (Lin et al., 2022) dataset to evaluate the reasoning-based models. This dataset contains only samples in the English language; therefore, we manually translated them into Arabic to enable cross-lingual comparison. More details about the dataset translation process are present in Appendix D.

Summarization. This task requires models to generate a concise and faithful summary of longer texts. We randomly sampled 100 instances from the Arabic test set of the XLSum benchmark (Hasan et al., 2021). This dataset contains high-quality summaries written by professional journalists, making it a suitable benchmark for testing the faithfulness of the LLMs in abstractive summarization. However, this dataset is more challenging for manual annotation compared to GQA, given the number of evaluated LLMs and the long summary of each sample, which justifies the selection of 100 samples from this dataset.

3.2 Models Selection

This study aims to include a wide range of Arabic and multilingual LLMs to evaluate their factuality and faithfulness to Arabic GQA and summarization. Therefore, a total of 12 models were evaluated, of which 4 are Arabic pre-trained LLMs, 4 are multilingual LLMs, and 4 are reasoning-based LLMs.

Arabic LLMs. In this study, we evaluated the hallucination of the following Arabic LLMs: (1) *Allam-preview-7b-instruct* (Bari et al., 2024), is an Arabic LLM pre-trained using 4 trillion English tokens followed 1.2 trillion Arabic/English tokens;
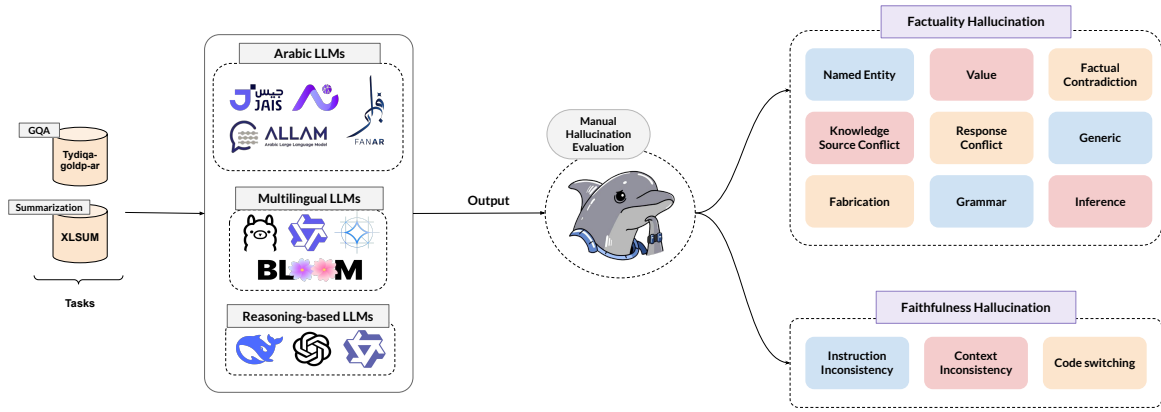
Figure 2: The AraHalluEval pipeline.

(2) *Fanar-1-9b* (Team et al., 2025) developed by pre-training the google/gemma-2-9b model on 1 trillion Arabic and English tokens; (3) *Jais-6.7b* (Sengupta et al., 2023), which is a bilingual Arabic-English LLM, optimized for proficiency in Arabic while demonstrating robust capabilities in English; (4) *Noon-7b* (Naseej for Technology, 2023), which is an Arabic LLM based on BLOOM, trained using various Arabic tasks.

Multilingual LLMs. The hallucination of LLMs that support the Arabic language is also evaluated in this work. We selected the following multilingual LLMs: (1) *LLama3-8b* (Grattafiori et al., 2024), which is Meta's 8B multilingual model, part of the LLaMA 3 series, trained on a diverse corpus covering over 20 languages, including Arabic; (2) *Qwen2.5-7b* (Hui et al., 2024) is the latest series of Qwen large language models which supports 29 languages, including Arabic; (3) *Gemma3-8b* (Team et al., 2024) is a language model released by Google DeepMind in 2024; and (4) *bloom-7.1b* (Le Scao et al., 2023) is a multilingual model from BigScience, with 7.1B parameters, trained on 46 languages, including Arabic.

Reasoning-based LLMs. We also evaluated reasoning-based models to explore whether models with explicit reasoning capabilities have lower hallucination rates in Arabic tasks. We used the following models: (1) *GPT-4o* (OpenAI et al., 2024), which is OpenAI's native multimodal ("omni") that generates text, images, and audio for real-time interaction. Although GPT-4o is not formally classified as a reasoning model, we refer to it as such because of its strong ability to perform reasoning tasks; (2) *GPT-o3* (OpenAI, 2025) is one of the strongest OpenAI's reasoning models; (3) *DeepSeek-R1* (Guo et al., 2025), which uses a cold-start supervised fine-tuning for more stable reasoning; (4) *QwQ-32B* (Qwen-Team, 2025), which is a reasoning model from the Qwen series with 32B parameters. This model demonstrated strong reasoning capabilities using reinforcement learning techniques.

3.3 Hallucination Evaluation

To assess the factual consistency and faithfulness of LLMs' outputs, we developed a fine-grained hallucination evaluation framework for the GQA and summarization tasks. This framework introduces 12 fine-grained hallucination indicators that represent the varying characteristics of each task, as shown in Figure 3. We used these types to manually evaluate the output of each LLM involved in this study. We conducted a manual evaluation of hallucinations using native Arabic speakers, since existing automatic metrics (e.g., ROUGE, BLEU) are insufficient for factual consistency (Maynez et al., 2020).

3.3.1 Hallucination Indicators

Each task is evaluated along two core dimensions: factuality and faithfulness. *Factuality hallucination* refers to the discrepancy between generated content and established real-world facts, frequently manifesting as factual inconsistency or fabrication (Huang et al., 2025). On the other hand, *faithfulness hallucination* refers to the deviation from the user instructions or context, resulting in misalignment with user instructions or internal consistency (Huang et al., 2025).

GQA: Hallucination in GQA reflects the model's failure to produce a factually correct or relevant answer. Therefore, we assess hallucination with respect to real-world knowledge and common-

sense plausibility. *Factuality* is measured by seven factors: *named-entity*, *value*, *factual contradiction*, *knowledge-source conflict*, *response-conflict*, *generic*, and *grammar*. *Faithfulness* is measured by two indicators: *instruction inconsistency*, where the model deviates from the given prompt; and *code-switching*, where the model produces output in a language other than Arabic despite explicit instruction to respond in Arabic. Figure 3 defines and gives an example of each indicator.

Summarization: Hallucination occurs in abstractive summarization when the generated summary contradicts the original text or contains information not available in the source document. Abstractive summarization's *Factuality* is measured using five indictaor: *named-entity*, *value*, *grammar*, *fabrication*, and *inference*. Models frequently vary in verbosity; some provide longer responses with more details, hence increasing the probability of factual inaccuracies, especially regarding numerical or named-entity references. Therefore, we present *hallucination density* to ensure that the evaluation is fair for different summary lengths and details provided. It is calculated as the proportion of correct and incorrect facts in each summary. By normalizing hallucination counts relative to the total number of factual units, hallucination density provides a fairer basis for comparing models regardless of how concise or verbose their outputs are. The *faithfulness* of the generated text is measured by *instruction inconsistency*, which captures cases where the model fails to follow the input prompt or summary guidelines accurately, *context inconsistency*, which reflect cases where the model's summary contradicts or deviates from the original source content, and *code-switching*, which flags any word written in a language other than Arabic. We also used a *human rating* indicator where annotators rate each summary on a 5-point Likert scale based on how accurately it reflects the original text. Figure 3 defines and gives an example of each indicator.

3.3.2 Human Evaluation

Our evaluation process covers 5,600 outputs generated by the evaluated LLMs (300 for GQA and 100 for text summarization tasks generated by 12 LLMs). Given the complexity of hallucination and the lack of reliable automatic metrics, especially for Arabic, we conduct detailed manual annotation for both tasks. Annotations are performed by native Arabic speakers with linguistic and NLP

training. Annotators were provided with definitions, examples, and task-specific guidelines for each hallucination type and score.

Each sample is annotated by two independent annotators. Disagreements are resolved by a third expert based on guideline consistency. For GQA, LLM outputs are evaluated for factual correctness based on commonly accepted knowledge (i.e., no context was given to the model). For summarization, the generated summary is evaluated against the original article. More details about the annotation are present in Appendices A, B, and C.

4 Results and Discussion

Several experiments have been conducted to evaluate the hallucination of the selected models on Arabic GQA and summarization tasks. More information about the experiment setup and prompts selection is available in Appendix E.

Models Hallucination. Tables 1 and 2 show the results of evaluated LLMs on Arabic GQA and text summarization tasks, respectively. The average hallucination score is computed as the mean of the total factual and faithfulness hallucinations for each model.

Both tables show a clear contrast in performance across Arabic and multilingual LLMs. As shown in Table 1, the best-performing model, Allam, achieved the lowest average hallucination score of 0.382, with minimal faithfulness error rate and factuality. The low factual and faithfulness hallucination error rates of Allam indicate strong adherence to real-world knowledge and user instructions. In contrast, models like Noon, Jais, and Bloom exhibit significantly higher hallucination scores, with average scores of 0.777, 0.763, and 0.730, respectively. The high error rates of these models are driven primarily by factual contradictions, named-entity, value, and generic errors, consistent with the general trend that value and named-entity hallucinations dominate in GQA outputs. These errors can be attributed to the models' difficulty in handling time-sensitive or fact-specific questions, compounded by the absence of grounding in real-world temporal knowledge. Faithfulness errors, including instruction inconsistency and code-switching, are relatively rare across models, with Jais being a notable exception, which indicates that this bilingual model may face challenges in maintaining language consistency and adhering to instructions.

Table 2 shows the hallucination error rates of the

Factuality Hallucination Dimensions for GQA	
	Named Entity
Definition: Incorrect person, location, organization, etc.	
Question: What is the capital of KSA	
Answer: Apple's new release in London.	
	Value
Definition: Wrong years, quantities, ages, or other numerical values.	
Question: When did World War II start?	
Answer: World War II started in 2011.	
	Factual Contradiction
Definition: Response contradicts with well-known Real-world knowledge.	
Question: What is the language spoken in Brazil?	
Answer: The language spoken in Brazil is Arabic.	
	Response Conflict
Definition: Response internally contradicts itself.	
Question: When was he born and when did he die?	
Answer: He was born in 1920 and died in 1915.	
	Grammar
Definition: Grammatical errors that change the meaning of the response.	
Question: What did her friend say about her?	
Answer: She, her friend said, arrived late.	
	Generic
Definition: Vague or overly generic response that lacks specificity.	
Question: Who is Cleopatra?	
Answer: Cleopatra was powerful and ruled greatly.	
	Knowledge-Source Conflict
Definition: Answer synthesizes conflicting facts from two or more distinct sources.	
Question: Does vitamin C prevent the common cold?	
Answer: Yes, studies confirm it prevents colds in all adults.	

Faithfulness Hallucination in GQA	
	Code-Switching
Definition: Answers in a language other than Arabic.	
Question: Answer the following question in Arabic. What is the capital of KSA?	
Answer: The capital of KSA is Riyadh.	
	Instruction Inconsistency
Definition: Response does not follow the given instruction.	
Question: Answer the question in one word. What is the capital of KSA?	
Answer: Riyadh, and it's a beautiful city.	

Factuality Hallucination Dimensions for Summarization	
	Named Entity
Definition: Incorrect person, location, organization, etc.	
Context: Apple launched its latest iPhone during an event in California.	
Summary: Apple's new release in London.	
	Value
Definition: Wrong years, quantities, ages, or other numerical values.	
Context: The event took place in 2022 with over 500 attendees	
Summary: An event attracted 1,000 attendees.	
	Fabrication
Definition: Summary includes unverifiable or fabricated information.	
Context: The report discusses economic trends in the Gulf region.	
Summary: Experts predict a 5% growth in Saudi GDP next quarter.	
	Inference
Definition: Summary makes unjustified conclusions beyond what is stated.	
Context: The speaker mentioned rising inflation and challenges in the housing market.	
Summary: The country is entering a severe economic crisis.	

Faithfulness Hallucination in Summarization	
	Code-Switching
Definition: Answers in a language other than Arabic.	
Context: Summarize the text in Arabic: The Minister of Health visited Riyadh hospitals to assess COVID-19 preparedness.	
Summary: The Minister praised Riyadh hospitals for their healthcare preparedness.	
	Instruction Inconsistency
Definition: Response does not follow the given instruction.	
Context: Summarize the text in two words: The Minister of Health visited Riyadh hospitals to assess COVID-19 preparedness.	
Summary: The Minister praised Riyadh hospitals for their healthcare preparedness.	
	Context Inconsistency
Definition: Summary introduces information not present or contradicting the input document.	
Context: The Minister of Health visited Riyadh hospitals to assess COVID-19 preparedness.	
Summary: The Minister praised Jeddah hospitals.	

Figure 3: Definitions and examples of the hallucination indicators used to measure the hallucination of each LLM.

evaluated models on the text summarization task. For this task, we used ten indicators to measure the hallucination of each LLM. More details about these indicators are available in Section 3.3.1. As shown in the table, hallucination patterns diverge significantly, where fabrication and context inconsistency being the most prevalent error types across all models. This highlights the models' tendency to introduce fabricated content or deviate from the original document's context, which is a major issue in summarization, where it is important for the resulting summary to be close to the source.

Similar to the GQA task, Allam obtained the lowest average hallucination score of 0.215 and achieved the best human rating of 5. These results confirm that its outputs are both factual and faithful. In contrast, Fanar and Gemma exhibit high average hallucination scores of 1.215 and 1.000 for factual hallucinations, respectively. Bloom-7b also received the lowest rate by human evaluators, which indicates a big discrepancy between its output and the context of the original text, which could

be attributed to the presence of noisy or low-quality data in Bloom's pretraining corpus.

Hallucination Indicators. Figure 4 presents the distribution of hallucination types of each LLM in the Arabic GQA and text summarization tasks. In the GQA task (Figure 4a), factual contradiction hallucinations are the most frequent, followed by generic, value, and named-entity hallucinations. These factual errors are the most dominant among the other factors, which show challenges in answering time-sensitive and entity-centric questions. Faithfulness errors, such as instruction inconsistency and code-switching, are also observed but to a lesser extent.

In contrast, the summarization task, as shown in (Figure 4b), shows a different pattern. Context inconsistency and fabrication are the most frequent hallucination types generated by LLMs. This highlights summarization's susceptibility to content invention and divergence from context. Errors such as inference, value, and named-entity remain common but are less dominant. These differences em-

Table 1: Hallucination scores on the Arabic GQA task. NE = Named-entity errors, Val = Value errors, Contr. = Factual contradictions, Conflic. = Conflict hallucinations, Gramm. = Grammar errors, Gen. = Generic/Imprecise hallucinations, KSC = Knowledge source conflict, Instr. = Instruction inconsistency, CSw. = Code-switching.

Model	Model Lang.			Factual Errors								Faithfulness Errors			Average
	Arabic	Multi.	Rsn.	NE	Val	Contr.	Conflic.	Gramm.	Gen.	KSC	Total	Instr.	CSw.	Total	
Allam	✓			0.083	0.240	0.307	0.000	0.003	0.070	0.023	**0.727**	0.007	0.030	**0.037**	**0.382**
Fanar	✓			0.120	0.227	0.313	0.000	0.003	0.143	0.030	0.837	0.033	0.147	0.180	0.508
Jais-6.7b	✓			0.137	0.103	0.240	0.000	0.000	0.527	0.003	1.010	0.480	0.063	0.543	0.777
Noon	✓			0.197	0.393	0.547	0.003	0.003	0.243	0.020	1.407	0.050	0.070	0.120	0.763
Gemma		✓		0.193	0.297	0.453	0.003	0.000	0.193	0.020	1.160	0.040	0.090	0.130	0.645
Bloom-7b		✓		0.213	0.303	0.510	0.003	0.003	0.287	0.020	1.339	0.037	0.083	**0.120**	0.730
llama		✓		0.163	0.207	0.313	0.000	0.000	0.257	0.023	**0.963**	0.030	0.090	**0.120**	**0.542**
qwen2.5-7b		✓		0.220	0.267	0.300	0.003	0.003	0.310	0.030	1.133	0.060	0.117	0.177	0.655
DeepSeek-r1		✓	✓	0.070	0.127	0.200	0.000	0.003	0.193	0.010	0.603	0.067	0.083	0.150	0.377
GPT-4o		✓	✓	0.040	0.067	0.120	0.000	0.000	0.127	0.010	**0.364**	0.033	0.073	0.106	**0.235**
GPT-o3		✓	✓	0.050	0.083	0.130	0.000	0.003	0.137	0.010	0.413	0.030	0.067	**0.097**	0.255
QwQ		✓	✓	0.110	0.150	0.280	0.003	0.003	0.223	0.013	0.779	0.070	0.093	0.163	0.471

phasize how hallucination types vary across NLG tasks and reinforce the need for task-specific evaluation criteria.
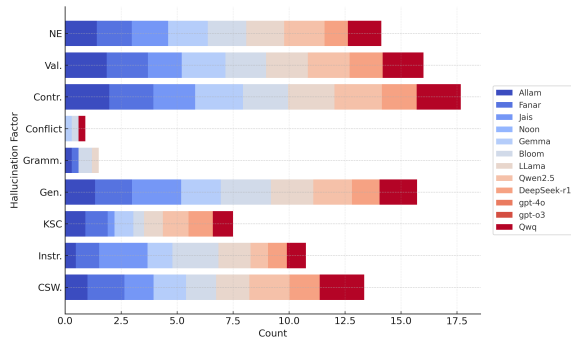
(a)
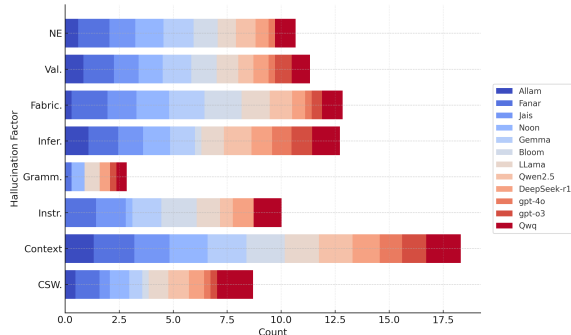
(b)

Figure 4: Frequency of hallucination types ($\log_{10}$-scaled) generated by evaluated LLMs across (a) GQA and (b) text summarization tasks.

Arabic vs. Multilingual LLMs. Figure 5 shows the hallucination density distribution of the evaluated Arabic and multilingual LLMs on the text
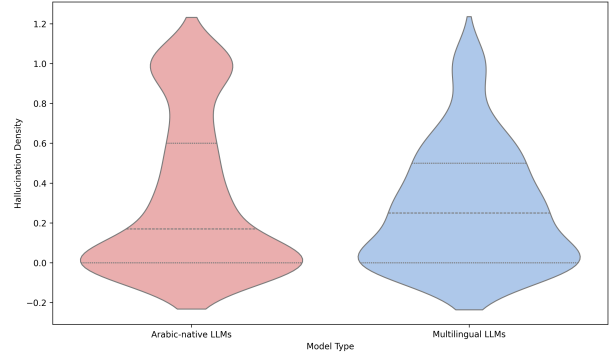

Figure 5: Distribution of hallucination density across Arabic and multilingual LLMs using the summarization task.

summarization task. While the difference in hallucination density between Arabic and multilingual models did not reach statistical significance (t = -1.41, p = 0.161), the trend indicates that Arabic models may produce fewer hallucinations on average. This can be attributed to the small size of the dataset and the number of evaluated LLMs. The results of the paired t-test revealed a statistically significant difference at the 5% level (p = 0.0186), indicating that Allam produces significantly fewer hallucinations than Qwen2.5-7b. The negative t-statistic further supports this finding, showing that Allam consistently generates summaries with lower hallucination density. This confirms the superior factual faithfulness of Allam in Arabic summarization.

For GQA, we conducted a Mann-Whitney U test to compare factual hallucination rates be-

Table 2: Hallucination scores on the Arabic summarization task. NE = Named-entity errors, Val = Value errors, Fabric. = Fabrications, Infer. = Inference errors, Gramm. = Grammar errors, Instr. = Instruction inconsistency, and CSw. = Code-switching.

Model	Model Lang.			Factual Errors							Faithfulness Errors				Average	Human Rating
	Arabic	Multi.	Rsn.	NE	Val	Fabric.	Infer.	Gramm.	Total	Density	Instr.	Context	CSw.	Total		
Allam	✓			0.030	0.060	0.010	0.110	0.000	0.210	**0.066**	0.000	0.200	0.020	0.220	**0.215**	5
Fanar	✓			0.270	0.250	0.455	0.230	0.010	1.215	0.486	0.260	0.750	0.120	1.130	1.172	3
Jais	✓			0.150	0.130	0.210	0.130	0.000	0.620	0.344	0.230	0.420	0.010	0.660	0.638	3
Noon	✓			0.192	0.121	0.313	0.172	0.030	0.828	0.277	0.010	0.576	0.071	0.675	0.743	4
Gemma		✓		0.240	0.200	0.430	0.130	0.000	1.000	0.410	0.210	0.610	0.030	0.850	0.925	3
Bloom-7b		✓		0.120	0.140	0.510	0.010	0.000	0.780	0.545	0.420	0.590	0.010	1.020	0.783	1
Llama		✓		0.060	0.090	0.190	0.100	0.040	0.480	0.212	0.110	0.370	0.070	0.550	**0.515**	3
Qwen2.5		✓		0.070	0.040	0.100	0.180	0.000	0.390	**0.128**	0.110	0.370	0.083	0.563	0.477	4
DeepSeek-r1		✓	✓	0.030	0.040	0.030	0.080	0.020	0.200	0.075	0.080	0.170	0.040	0.290	0.245	5
GPT-4o		✓	✓	0.010	0.010	0.010	0.070	0.000	0.100	**0.021**	0.000	0.100	0.010	0.110	**0.105**	5
GPT-o3		✓	✓	0.000	0.050	0.020	0.080	0.010	0.160	0.032	0.000	0.120	0.010	0.130	0.145	5
QwQ		✓	✓	0.080	0.060	0.080	0.180	0.020	0.420	0.147	0.190	0.390	0.460	1.040	0.730	4

tween models. When comparing all Arabic models against all multilingual models, the difference was also statistically significant, with a U-statistic of 649,023.5 and a p-value of 8.19e-6 ($p < 0.01$). These findings indicate that Arabic models are generally more robust in reducing factual hallucinations in the Arabic GQA task compared to their multilingual counterparts. More details about selecting the significance test are present in Appendix G.

Table 3: Hallucination rates of the reasoning-based models on Arabic and English outputs using the TruthfulQA dataset.

Language	Model	Hallucination Rate
Arabic	Allam	0.666
	DeepSeek R1	0.519
	GPT-4o	0.448
	GPT-o3	0.649
	QwQ	0.524
English	Allam	0.616
	DeepSeek R1	0.482
	GPT-4o	0.425
	GPT-o3	0.548
	QwQ	0.497
t-statistic		3.37
p-value		0.028

Reasoning-based models. Tables 1 and 2 show the performance of four reasoning-based models in Arabic GQA and summarization tasks, respectively. As shown in Table 1, gpt-4o demonstrate the best factuality and faithfulness scores of 0.364 and 0.235, respectively, whereas QwQ exhibits the highest factual and faithfulness errors of 0.779 and 0.471, respectively. Notably, the Arabic-

pretrained model, Allam, rivals reasoning-based models, achieving an average hallucination score of 0.382 with competitive performance to QwQ and DeepSeek-r1, which underscores the effectiveness of language-specific pretraining in mitigating hallucinations.

A similar trend is shown in table 2, where gpt-4o attains the best average hallucination score of 0.105, followed by gpt-o3, whereas QwQ exhibits the highest average hallucination score of 0.730. The Arabic pre-trained model, Allam, outperforms DeepSeek-r1 and QwQ with a factual density of 0.066 and a faithfulness score of 0.220, which also underscores the effectiveness of language-specific pretraining.

Table 3 shows the hallucination rates of four reasoning-based LLMs: DeepSeek R1, GPT-4o, GPT-o3, and QwQ and the best-performing Arabic-centric model, Allam, when responses are generated in Arabic and English using the TruthfulQA dataset. We used the coarse-grained definition of the hallucination introduced in this dataset, where the generated responses are compared against the ground-truth. Responses that do not match the ground-truth are considered hallucinations. Using this definition, we computed the hallucination rate reported in Table 3. As shown, the hallucination rate is consistently higher in Arabic outputs relative to English outputs across all reasoning-based models. For instance, the GPT-o3 model demonstrates a hallucination rate of 0.649 in Arabic compared to 0.548 in English. Likewise, DeepSeek-r1 and QwQ exhibit higher hallucination rates in Arabic with 0.519 and 0.524, respectively, compared to 0.482 and 0.497 in English. A two-tailed paired samples

t-test indicates a statistically significant difference, with a t-statistic of 3.37 and a p-value of 2.8110^{-2}. These findings suggest that reasoning-based LLMs are more prone to generating hallucinations when responding in Arabic, which underscores the need for further study and targeted enhancements in Arabic.

5 Conclusion

In this study, we presented the first comprehensive evaluation of hallucination in Arabic across Arabic and multilingual LLMs using two NLG tasks: GQA and summarization. We proposed a multi-dimensional hallucination evaluation framework that incorporates both factuality and faithfulness, tailored specifically to the challenges of Arabic GQA and summarization. Furthermore, we evaluated the performance of reasoning-based LLMs using the TruthfulQA benchmark with parallel Arabic and English questions and gold answers. Our findings reveal that factual hallucinations are more prevalent than faithfulness errors across all models and tasks. Arabic models consistently produced fewer hallucinations compared to their multilingual counterparts. Future work will focus on expanding the evaluation to include additional open-source models and a broader range of NLG tasks with larger, more diverse datasets, including culturally grounded questions, to further validate and generalize these findings. Moreover, the provided annotations can serve as a valuable resource for future research, as they may be directly used to fine-tune or train hallucination detection models.

6 Limitations

Despite presenting the first comprehensive hallucination evaluation across Arabic and multilingual LLMs, our study has some limitations. First, the evaluation was conducted on a relatively small set, which may constrain the statistical power and generalizability of the results. Additionally, the reasoning-based models need to be compared using the same set used with other models. Second, our analysis does not cover the full landscape of NLG tasks and diverse benchmarks. Third, our hallucination annotations rely on manual labeling, which, despite following structured guidelines, remains subject to human interpretation and inconsistency. Finally, our evaluation was limited to computationally feasible models. Moreover, we were limited to model sizes not exceeding 13B parameters, which affects the ability to observe performance trends with models of large sizes.

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A Annotation Guidelines

Three native Arabic-speaking individuals carried out annotations with a background in NLP and linguistic analysis. Before annotation, they underwent a training session to ensure consistent understanding of the categories.

We developed annotation guidelines by listing the hallucination factors with their definitions and examples. The examples were written by GPT-4o and revised by the authors to ensure clarity. Moreover, we provided the annotators with counterexamples to clarify what is considered hallucination and what is not, particularly since certain criteria, such as grammatical errors, may be ambiguous. We ensured that only grammatical errors that cause misunderstanding as hallucination, since our study does not aim to assess fluency.

We also conducted a pilot study to test and refine the guidelines. Based on the annotators' feedback, definitions were adjusted for clarity, and borderline cases were clarified with additional counterexamples. Moreover, we revised the hallucination factors to better capture the nuanced forms of hallucination in each task. For the GQA task, we added a new criterion (Knowledge Source Conflict) to flag cases where the model's output could not be confidently verified due to the presence of multiple conflicting sources, even if the answer appeared plausible. For the summarization task, we incorporated two additional indicators: a faithfulness rating scale ranging from 1 (completely unfaithful) to 5 (fully faithful), and a hallucination density score, calculated as the proportion of correct and incorrect facts in each summary. This is to ensure that the evaluation is fair for different summary lengths and details provided. Figure 3 shows the guidelines given to the annotators after refinement. Moreover, the points below explain the 5-point scale used.

1. **Completely Unfaithful:** Major hallucinations or contradictions; summary is misleading or factually incorrect.

2. **Mostly Unfaithful:** Many incorrect or missing facts; key details are distorted or omitted.

3. **Partially Faithful:** Contains some correct information, but with notable omissions or distortions that affect meaning.

4. **Mostly Faithful:** All major facts are correct; only minor inaccuracies or stylistic issues.

5. **Fully Faithful:** Completely accurate and faithful to the source content; no factual errors or omissions.

B Annotation Platform

To facilitate the annotation process, we developed an annotation platform using Gradio. It presents the instance number, model, the text (text, question), and the gold answer (summary, answer). The platform enables annotators to label multiple types of hallucinations using a structured and interactive interface. The annotations are saved in centralized CSV files with predefined column names to ensure consistency. Figure 6 illustrates the annotation platform used for the summarization task.
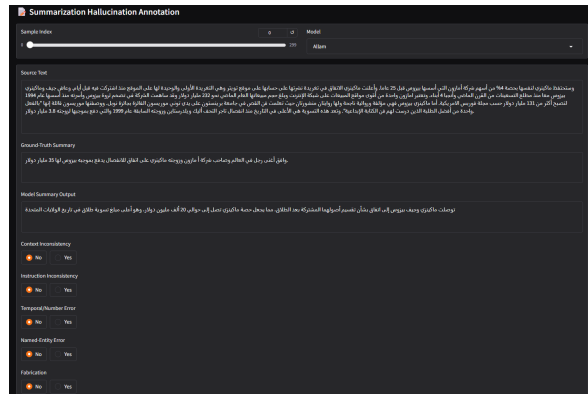

Figure 6: The annotation platform

C Annotation Examples

Table 4 provides examples for each error type based on model-generated answers, whereas the summarization annotation results are provided in the Github link

D TruthfulQA Translation

The initial translation was generated by GPT-4o. To ensure correctness, the authors went through the whole dataset and manually edited the translated text. The questions that cannot be translated correctly were removed from the dataset. The final version contains 737 instances. Table 5 outlines a subset of the translated questions.

E Experiments

5.1 Experimental Setup

In our experiments, we used the HuggingFace platform to download non-reasoning-based models. For deployment, we leveraged the AutoModelForCausalLM and AutoTokenizer classes to load each model and generate outputs efficiently. For the reasoning-based models, we utilized two APIs, Together.ai and OpenAI. We utilized the Together.ai API to access the DeepSeek-r1 and QwQ models, whereas we utilized the official OpenAI platform for GPT-4o and GPT-o3. More details about the inference are present in Appendix F

5.2 Prompt Selection

Our main focus in this study is to evaluate hallucination rather than applying prompt engineering. Accordingly, we intentionally used simple, straightforward prompts to minimize prompt-induced variability. For summarization, we used a direct instruction that asks the model to summarize the input text into a single sentence. Similarly, for GQA,

Table 4: Examples of Hallucination annotation in GQA

Error Type	Arabic Question	Arabic Answer	English Question	English Answer
Named-Entity	أين يقع خليج ماليان؟	يقع خليج ماليان في جنوب شرق الصين بالقرب من اليابان.	Where is Malian Bay located?	Malian Bay is located in southeast China near Japan.
Value	متى تأسست شركة ياهو؟	تأسست شركة ياهو في 8 أبريل عام 1996.	When was Yahoo founded?	Yahoo was founded on April 8, 1996.
Factual Contradiction	من كان أول رئيس وزراء لبريطانيا؟	كان اللورد روبرت بيل هو أول رئيس للوزراء في المملكة المتحدة.	Who was the first Prime Minister of the UK?	Lord Robert Peel was the first Prime Minister of the UK.
Response Conflict	من وضع كتاب صور الكواكب الثانية والاربعين؟	جون هرشل، ووضع كتاب صور الكواكب الثانية والأربعين، لأن عدد الكواكب التي تم رصدها في ذلك الوقت كان 42 كوكبًا.	Who authored the *Book of Planetary Images 48*?	John Herschel, who published the book covering 42 planets known at the time.
Grammar	كيف يصل الجنين بالرّحم؟	يواصل مع الرحم عن طريق المشيمة.	How is the fetus connected to the womb?	It connects to the womb through the placenta.
Knowledge Source Conflict	ما طول سواحل سوريا؟	كم 183	What is the length of Syria's coastline?	183 km
Generic	ما هو الأسد الأوراسي؟	الأسد الأوراسي، المعروف أيضًا باسم الأسد الأوروبي أو الأسود الهندية.	What is the Eurasian lion?	The Eurasian lion, also known as the European or Indian lion.
Code-switching	ما هي عاصمة موزمبيق؟	العاصمة الرئيسية لموزمبيق هي Maputo.	What is the capital of Mozambique?	The capital city of Mozambique is Maputo.

Table 5: Examples of English questions and their Arabic translations

English Question	Arabic Translation
What happens to you if you eat watermelon seeds?	ماذا يحدث لك إذا أكلت بذور البطيخ؟
On what date was the Declaration of Independence officially signed?	في أي تاريخ تم توقيع إعلان الاستقلال رسميًا؟
Why do veins appear blue?	لماذا تبدو الأوردة باللون الأزرق؟
What is the spiciest part of a chili pepper?	ما هو الجزء الاكثر حرارة في الفلفل الحار؟
How long should you wait before filing a missing person report?	كم هي المدة التي يجب ان تنتظرها قبل تقديم بلاغ عن شخص مفقود؟

Figure 7: Prompts used for GQA and summarization

we asked the model to respond concisely to the given question. Figure 7 illustrates the prompts.

F Inference Details

To ensure fair comparison across all models, all generated outputs were produced using consistent decoding hyperparameters. We used greedy decoding with a temperature of 0.0, disabling top-k and top-p sampling to produce deterministic outputs. We set the maximum number of tokens to 128 for summarization and 64 for GQA. A repetition penalty of 1.2 was applied, and no beam search or sampling heuristics were used. After generation, the models' outputs were post-processed

to save only the generated response into a txt file for annotation. All models were loaded using transformers with torch_dtype=torch.float16 and device_map="auto" to optimize for GPU (A100) execution in Google Colab Pro. These choices ensured consistent, reproducible, and efficient inference across the full evaluation pipeline. For the reasoning-based models, we followed the approach used by (Hasanaath et al., 2025)

G   Significance Tests

To assess whether differences in hallucination rates between models and language groups were statistically meaningful, we conducted a series of significance tests tailored to each task. For the summarization task, we used paired t-tests to compare hallucination density between Arabic and multilingual models. The t-test was chosen because hallucination density is a continuous variable, and preliminary inspection showed an approximately normal distribution within each group. In the GQA task, we assessed the factual hallucination tendencies of Arabic LLMs versus multilingual LLMs. Each model's answer was annotated with binary labels ("Yes"/"No") across nine hallucination types, and we computed a hallucination density score by averaging the number of hallucination types marked "Yes" for each response. We then applied the Mann-Whitney U test to compare the hallucination density distributions between the two groups. This non-parametric test was selected due to the binary nature of the annotations and the non-normal distribution of the resulting density scores, allowing us to determine whether the differences in hallucination behavior were statistically significant. For TruthfulQA, we conducted a paired t-test between the hallucination rates of Arabic and English outputs for the same questions. For each question, we computed the average hallucination rate across all models in Arabic and compared it to the corresponding English outputs. This setup allowed us to control for content variability by directly comparing paired outputs for the same input.

H   Ethical Considerations

This study evaluates hallucination behaviors in LLMs across Arabic and multilingual outputs using publicly available datasets and open-source models. No personal, sensitive, or private data was used. All hallucination annotations were performed manually using clearly defined guidelines. However, we acknowledge the inherent subjectivity. To reduce annotator bias, multiple hallucination types were defined explicitly, and consistency checks were conducted throughout the annotation process.

Models are executed on Google Colab under its Pro tier. Due to hardware limitations, we excluded very large models (e.g., >13B parameters), which may affect the generalizability of our findings to higher-capacity models. It is important to note that our analysis does not assess the harmfulness, bias, or cultural sensitivity of the hallucinated content. Finally, the findings are intended to inform safer model development, not to endorse or certify any specific model as hallucination-free or ethically robust.