MedHalwasa: Quantify & Analyze Factual Hallucinations in Large Language Models For Arabic Medical Data

Anonymous ACL submission

Abstract

Hallucination in medical text generation poses critical risks, especially when large language models (LLMs) produce factually incorrect information. Such behavior, particularly when occurring at scale, can affect the quality of clinical decision-making and compromise patient safety. Although this issue has been studied in English, it remains largely unexplored in Arabic. We introduce ***MedHalwasa***, the first Arabic dataset to quantify and analyze hallucination in Arabic medical fact generation. The name *MedHalwasa* is derived from "Medical Halwasa," where "Halwasa" denotes hallucination in Arabic. Using nine different LLMs, we generate and evaluate 9,000 Arabic medical facts, annotating them with automatic factuality annotations. To support future research, we detail a systematic and reproducible data generation and annotation framework that can be extended to study other LLMs and domains. Our study enables the first systematic analysis of hallucinations in Arabic medical contexts and offers key insights to inform the selection of reliable LLMs for Arabic healthcare applications. The dataset is publicly accessible to facilitate future research[1].

1 Introduction

The rise of foundation models has marked a turning point in the field of Artificial Intelligence (AI), unlocking new possibilities across a broad spectrum of applications. Among these, Large Language Models (LLMs) have stood out for their ability to perform a wide array of natural language processing (NLP) tasks such as summarization, translation, question answering, and text generation with impressive fluency and coherence. By learning patterns from massive amounts of general and domain-specific text, LLMs have shown not only linguistic competence but also surprising adaptability, making them increasingly appealing for deployment in sensitive and high-impact areas such as healthcare.

Despite their remarkable capabilities, LLMs are prone to a critical limitation commonly referred to as hallucination, the generation of information that appears fluent and convincing yet is factually incorrect or unverifiable (Rawte et al., 2023)(Ji et al., 2023). Previous research (Huang et al., 2025b) has broadly classified hallucinations into two main categories: factuality hallucination, where the generated content conflicts with known or verifiable real-world facts, and faithfulness hallucination, where the output deviates from the given input or exhibits internal inconsistency. These distinctions underscore the complexity of the hallucination problem and highlight the pressing need for robust mechanisms to detect, quantify, and mitigate hallucinations.

In general-purpose applications, such outputs may be relatively harmless; however, in medical contexts, hallucinations carry far more serious implications. They can misguide clinical decision-making, misinform patients, and ultimately pose risks to patient safety. Hallucinated medical content may include incorrect dosages, fabricated conditions, or misleading interpretations of diagnostic criteria, all of which have the potential to cause real-world harm (Kim et al., 2025).

Although numerous studies have investigated the risks of hallucination of LLMs in the medical domain for English (Agarwal et al., 2024) (Ahmad et al., 2023) (Ziaei and Schmidgall, 2023a), there remains a limited understanding of how this problem manifests in medium and low-resource languages such as Arabic, where the impact may be equally, if not more, concerning due to the scarcity of language-specific resources and benchmarks (Silly et al., 2025).

The need for deeper investigation into hallucinations in LLMs within the context of Arabic medical information is underscored by both the linguistic

[1] Available upon request

complexity of Arabic and the critical importance of accurate medical communication. Addressing hallucinations in this setting is not only essential for enhancing the reliability and trustworthiness of LLMs but also holds significant implications for deploying such models in regions with limited medical infrastructures and low-resource healthcare systems. Therefore, the motivation behind our work is twofold: (1) to enable a rigorous and reproducible evaluation of the factuality and reliability of LLMs when generating medical content in Arabic, and (2) to pave the way for developing robust techniques to detect and mitigate hallucinations in Arabic medical LLMs.

This paper aims to bridge the current understanding gap by conducting a comprehensive study on hallucinations in the generation of Arabic medical texts. Using a diverse set of LLMs with varying architectures, sizes, and training characteristics, we seek to answer the following research questions.
I) To what extent can we rely on the factual accuracy of medical content generated by LLMs in Arabic?
II) Do specific model attributes (e.g., model size, training language mix, or reasoning capabilities) play a consistent role in mitigating factual hallucinations?
III) Which medical domains and concepts are most susceptible to factual hallucinations in Arabic texts, and what types of hallucination errors explain these failures?

2 Related Work

Hallucinations in Medical Text Generation. Hallucinations in medical text generation present unique challenges compared to those in general domains (Kim et al., 2025). They often appear in critical tasks such as diagnosing conditions, recommending treatments, or interpreting laboratory results, where even small inaccuracies can have serious consequences for patient care. What makes them particularly concerning is that these errors often sound plausible and include specialized medical terms, which can make them difficult to spot without expert knowledge. As healthcare systems begin to integrate AI more deeply into clinical workflows, the risk of such hallucinations going unnoticed becomes even more pressing.

A growing body of research has examined hallucinations in large language models within the medical domain, emphasizing the serious risks posed by factually inaccurate outputs that can undermine clinical decision-making and compromise patient safety (Agarwal et al., 2024; Ahmad et al., 2023; Ziaei and Schmidgall, 2023b). In response, several benchmarks have been proposed to systematically detect and evaluate hallucinations in medical LLMs on a variety of task types, input modalities, and evaluation protocols (Agarwal et al., 2024).

One such benchmark is Med-HALT (Umapathi et al., 2023), which evaluates hallucinations in LLMs through two categories of tests: Reasoning Hallucination Tests (RHTs) and Memory Hallucination Tests (MHTs), designed to assess models' capabilities in problem-solving and information recall. Meanwhile, HALT-MedVQA (Wu et al., 2024) investigates hallucinations in large vision-language models (LLVMs) and introduces a dataset of medical images paired with question-answer sets. HALT-MedVQA focuses on three core tasks: FAKE Question, None of the Above (NOTA), and Image SWAP, and evaluates model performance primarily using LLaVA-based architectures (Liu et al., 2023).

In the context of non-English medical data, the Chinese Medical Hallucination Evaluation Benchmark (CMHE) (Dou et al., 2024) offers a comprehensive evaluation to understand and mitigate hallucination issues in Chinese medical LLMs. It identifies a crucial issue called "snowballing hallucination", where LLMs generate more errors when encountering initial misinformation. The CMHE benchmark features three primary tasks: detecting hallucinations, diagnosing diseases in complex scenarios, and explaining medical concepts, using specific medical glossaries such as ICD-10 and MeSH for robust evaluation.

Several other benchmarks have also contributed to this emerging field by providing structured evaluations of hallucinations in both LLMs and vision-language models (Gu et al., 2024; Chen et al., 2024; Manes et al., 2024; Addlesee, 2024; Hegselmann et al., 2024; Zuo and Jiang, 2024). Together, these efforts offer important tools and insights for understanding and mitigating hallucination risks in medical AI systems.

Hallucinations in Arabic Text Generation. Despite the growing interest in hallucinations produced by LLMs in high-resource languages, relatively few studies have investigated this phenomenon in Arabic, a morphologically rich and syntactically complex language that presents dis-

tinct challenges for language modeling. Halwasa (Mubarak et al., 2024) introduced the first Arabic data set specifically designed to quantify and analyze hallucinations in LLM output. This work focuses on open-ended text generation and evaluates two OpenAI models, with generated outputs manually annotated for factual accuracy, correctness, and linguistic quality. While Halwasa targets sentence-level hallucinations in Arabic, HalluVerse25 (Abdaljalil et al., 2025) offers a multilingual benchmark that includes fine-grained hallucination categories across English, Arabic, and Turkish.

Hallucinations in Arabic Medical Text Generation. To the best of our knowledge, the intersection of medical hallucinations and Arabic text generation remains largely underexplored, with no existing datasets or benchmarks dedicated to evaluating factual consistency in this critical setting. Moreover, existing research shows that while LLMs may be capable of detecting hallucinations, this ability does not necessarily prevent them from generating hallucinated content in the first place (Dou et al., 2024). In light of these gaps, we introduce *MedHalwasa*, a dataset designed to evaluate the factuality of Arabic medical content generated through open-ended generation. Unlike previous work that tests the ability of LLMs to detect hallucinations, our focus is on assessing the likelihood that the models generate hallucinated medical information in the first place.

3 Data Generation

To assess the factuality of the Arabic medical content generated by large language models, we design *MedHalwasa* data generation and evaluation framework in three main stages as shown in Figure 1. These stages are further decomposed into five key steps: (1) generation of medical vocabulary, (2) LLM selection strategy, (3) data generation protocol, (4) factuality evaluation, and (5) results analysis.

Medical Vocabulary Generation. To ensure broad coverage across medical subdomains, we selected 200 of the most common and frequently queried medical terms relevant to the general public, where factual reliability of LLMs has the greatest practical impact. We employed structured prompting with ChatGPT to obtain an initial list of Arabic medical terms (Figure 2). To ensure that this vocabulary is not specific to ChatGPT's knowledge base, we further prompted Arabic-focused and multilingual models (Qwen2.5-Max (Team, 2024), DeepSeek-R1 (DeepSeek-AI et al., 2025), and Fanar (Team et al., 2025)) to independently generate comparable lists. LLMs are trained on vast corpora of web data, including Arabic medical queries, forums, and health websites, which inherently capture real-world user patterns. The high similarity rates with our ChatGPT-generated list (92% with Qwen2.5-Max, 84.5% with DeepSeek-R1, and 73% with Fanar) demonstrate strong inter-model agreement on a core medical vocabulary relevant to Arabic speakers. In addition, we conducted manual verification of the 200 terms with four native Arabic speakers, two from a patient/user perspective and two with medical expertise, who all confirmed that the overall vocabulary is valid and representative of commonly used Arabic medical terminology.

Large Language Model Selection Strategy. We choose a diverse set of LLMs to reflect different behaviors in Arabic medical fact generation. Our selection covers key aspects such as model size, accessibility (open-source vs. closed-source), language scope (bilingual vs. multilingual), and specialization (reasoning-focused vs. general-purpose). The models we evaluate include GPT-4o (OpenAI et al., 2024b), o1 (OpenAI et al., 2024a), Qwen2.5-Max (Team, 2024), DeepSeek-R1 (DeepSeek-AI et al., 2025), jais-adapted-70b (Inception, 2024), Llama-3.3-70B-Instruct (Grattafiori et al., 2024), Llama-3.1-8B-Instruct (Grattafiori et al., 2024), BiMediX2-8B-hf (Mullappilly et al., 2024), and Fanar (Team et al., 2025).

Data Generation Protocol. With the defined vocabulary and models, we implement a unified data generation protocol to ensure consistency between models. Following (Mubarak et al., 2024), each model is prompted to generate five verifiable factual sentences per Arabic medical term, yielding a total of 1,000 factual statements per model. We refer to this aggregated dataset of 9,000 Arabic medical factual sentences as the *MedHalwasa* dataset. The prompt structure used across all models is shown in Figure 3.

Due to differences in model availability and behavior, we use three distinct interaction methods: (1) API calls for GPT-4o, o1, Fanar, Llama-3.1-8B-Instruct, Llama-3.1-8B-Instruct, and BiMediX2-

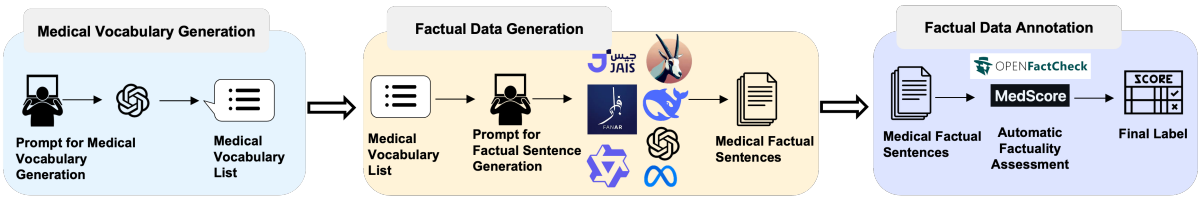

Figure 1: Overview of the *MedHalwasa* dataset construction and evaluation pipeline. It comprises three main stages: (1) Arabic medical vocabulary generation using ChatGPT, (2) factual data generation, where multiple LLMs produce Arabic medical sentences based on the vocabulary list, and (3) data annotation, where automatic factuality assessment frameworks assign factuality labels to the generated sentences.

Provide me a list of 200 Arabic medical terms queried by individuals seeking medical information or checking medical presuppositions that are frequently used in hospitals and online platforms. list the terms as follows :

Arabic medical term , English translation of Arabic medical term

Figure 2: Prompt used in Chat-GPT for Arabic medical terms generation.

Give exactly FIVE Arabic complete and diverse factual sentences having the following term: {term}. These sentences should have facts that can be checked and verified. Write the sentences separated by a new line without translation and without numbering.

Figure 3: Prompt used in the nine selected LLM models to generate the *MedHalwasa* dataset.

8B-hf (2) local hosting for Jais-70b, and (3) web-based prompting through Macro Recorder for models with undesirable behavior when called via the API, such as Qwen2.5-Max and DeepSeek-R1. Some of the models exhibit language inconsistencies, occasionally mixing Arabic with English, Russian, or Chinese text. Others generate improperly formatted outputs (e.g., a paragraph instead of separate facts). To address these inconsistencies, we generate multiple runs when needed and select the most suitable output from among them.

Factuality Assessment. To evaluate the factual accuracy of the generated Arabic medical sentences in the *MedHalwasa* dataset, we designed our factuality annotation strategy with real-world usage in mind: millions of Arabic speakers, including healthcare professionals, are already turning to LLMs for medical information in Arabic, even though these models are primarily trained on English data. In this high-stakes setting, relying solely on costly domain-expert annotation would make evaluation slow and difficult to scale, preventing timely assessment as new models continue to emerge. Our automatic and reproducible pipeline enables scalable benchmarking of diverse models—including proprietary, multilingual, Arabic-centric, and healthcare-specialized LLMs (e.g., GPT-4o, o1, DeepSeek-R1, LLaMA, Fanar, Jais, BiMediX), and can be readily extended to larger vocabularies and additional languages.

We employ two complementary fact-checking frameworks: OpenFactCheck (Iqbal et al., 2024) and MedScore (Huang et al., 2025a). Both follow a decompose-then-verify strategy designed for free-form answers. OpenFactCheck decomposes sentences into atomic claims, retrieves supporting evidence from external sources (Google Search, Wikipedia, GPT-based retrieval), and assigns a strict binary factuality label (True/False). MedScore, tailored to the medical domain, decomposes responses into condition-aware clinical facts and verifies them using both general-purpose and medical-specialized models, producing a continuous score (0–1) reflecting the proportion of true claims. Together, these methods provide both conservative (binary) and nuanced (continuous) measures of factuality.

To further strengthen confidence in this automated approach, we conducted manual verification of 15% of randomly selected samples from the dataset, carried out by native Arabic speakers from a patient/user perspective. This manual check is to confirm the validity of the automatic evaluations while verifying their ability to scale to larger vocabularies and newly released models without requiring constant human involvement.

Finally, it is important to clarify that the factuality scores are not intended as exact clinical labels but as robust estimations of relative reliability across models. By employing two independent fact-checking frameworks and observing consistent trends between them, we ensure that the conclusions about model performance remain reliable and actionable for improving Arabic medical applications.

Arabic Medical Term	English Medical Term
التهاب الحلق	Sore throat
التهاب اللوزتين	Tonsillitis
ارتفاع ضغط الدم	Hypertension
انخفاض ضغط الدم	Hypotension
السكري	Diabetes
السكتة الدماغية	Stroke
النوبة القلبية	Heart attack
انسداد الشرايين	Artery blockage

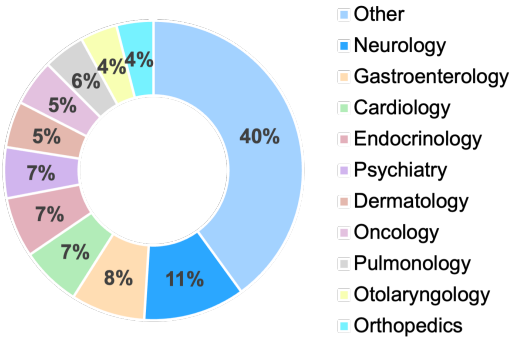

Figure 4: Top: The table on the top presents a subset of Arabic medical terms along with their corresponding English translations. Bottom: A donut chart showing the distribution of terms across the ten most frequent medical domains in the dataset; the remaining 25 domains are grouped under "Other".

Medical Term	Index	Generated Sentences
التهاب الحلق	1	يعتبر التهاب الحلق من الأمراض الشائعة التي تصيب الإنسان، وهو يحدث نتيجة لعدوى فيروسية أو بكتيرية في منطقة البلعوم والحنجرة.
التهاب الحلق	1	يمكن أن يتسبب التهاب الحلق بأعراض مثل الألم وصعوبة البلع وارتفاع درجة الحرارة والصداع والتعب العام.
التهاب الحلق	1	يتم علاج التهاب الحلق عادة باستخدام المضادات الحيوية إذا كان السبب بكتيريا، بينما تستخدم الأدوية المضادة للفيروسات لعلاج العدوى الفيروسية.
التهاب الحلق	1	يجب على الأشخاص الذين يعانون من أعراض حادة لالتهاب الحلق مراجعة الطبيب للحصول على التشخيص الصحيح والعلاج المناسب.
التهاب الحلق	1	ينصح بتناول السوائل الدافئة والغرغرة بالماء المالح لتخفيف الأعراض المصاحبة لالتهاب الحلق والحفاظ على ترطيب الفم والحلق.
التهاب اللوزتين	2	يمكن أن يحدث التهاب اللوزتين بسبب عدوى بكتيرية أو فيروسية، ويمكن أن يسبب أعراضًا مثل الألم في الحلق وصعوبة البلع والحمى وتضخم الغدد الليمفاوية في الرقبة.
التهاب اللوزتين	2	يتم علاج التهاب اللوزتين البكتيري عادة بالمضادات الحيوية، بينما يعالج الفيروسي بالراحة وتناول السوائل الدافئة والمسكنات لتخفيف الأعراض.

Figure 5: A sample from the *MedHalwasa* dataset showcasing generated Arabic medical factual sentences. Each row includes a medical term, its index (indicating the vocabulary group), and a corresponding factual sentence generated by an LLM. For each term, five different factual sentences are created to capture diverse factual expressions.

4 Results

4.1 Medical Vocabulary and Data Generation

A sample from the generated list of 200 Arabic medical vocabulary is presented in Figure 4. By carefully engineering the prompt, we ensured that the extracted vocabulary encompasses a broad range of commonly queried medical terms, spanning symptoms, conditions, treatments, and diagnostics frequently encountered in hospitals and online health platforms, corresponding to various medical domains. In total, there are 35 medical domains covered by the 200 medical terms. This comprehensive vocabulary base enables the generation of diverse and contextually rich factual statements in the *MedHalwasa* dataset, as illustrated in Figure 5.

4.2 Factual Accuracy of Generated Content

To assess the reliability of large language models in generating factual medical content in Arabic, we evaluate their factual accuracy. Table 1 presents a comparative evaluation of various large language models on the task of generating factual Arabic medical statements. We report performance using two factual evaluation frameworks: MedScore, which is specifically designed to assess medical factuality (Huang et al., 2025a), and OpenFactCheck, a domain-agnostic factuality framework applicable across various topics, including medicine (Iqbal et al., 2024) where both metrics show consistent relative rankings across models.

The table is sorted by MedScore values and divided into two groups: large-scale models and medium/small-scale models. Among the large models, Qwen2.5-Max achieves the highest MedScore (97.6%), demonstrating strong capability in generating factually accurate medical content in the Arabic language. This is followed by GPT-4o and o1 OpenAI models, both achieving a MedScore of 95.1%, with o1 distinguished by its reasoning capability. Deepseek-R1, a large open-source model (671B parameters), scores slightly lower (94.1%). However, this model activates a significantly smaller number of parameters at inference time. These results suggest that while reasoning capabilities are intended to improve factuality, in practice, they do not always translate to superior performance. Instead, models like Qwen2.5-Max and GPT-4o, although not explicitly labeled as reasoning models, demonstrate a stronger overall factual accuracy in the Arabic medical domain.

In the medium and small model category, Fanar-9B achieves the highest MedScore (92.3%), showcasing that a well-curated and culturally aligned bilingual (English-Arabic) model can compete ef-

Model	Size	Type	MedScore	OpenFactCheck
Qwen2.5-Max	**325B**	**Multilingual/Open Source**	**97.6%**	**94.2%**
GPT-4o	–	Multilingual/Closed Source/VLM	95.1%	90.1%
o1	–	Multilingual/Closed Source/Reasoning/ VLM	95.1%	89.0%
Deepseek-R1	671B	Multilingual/Open Source/Reasoning	94.1%	85.7%
Fanar	9B	Bilingual/Open Source	92.3%	81.3%
jais-adapted-70b	70B	Bilingual/Open Source	91.9%	82.8%
Llama-3.3-70B-Instruct	70B	Multilingual/Open Source	86.5%	72.4%
BiMediX2-8B-hf	8B	Bilingual/Open Source/VLM	76.8%	57.5%
Llama-3.1-8B-Instruct	8B	Multilingual/Open Source	50.5%	40.9%

Table 1: Performance comparison of the factual accuracy of different LLMs in generating Arabic medical sentences, evaluated using MedScore and OpenFactCheck over 1,000 samples per model.

fectively with significantly larger systems. Fanar is based on Google's Gemma-2-9B (Team et al., 2024) and has been continually pretrained with particular attention to Modern Standard Arabic (MSA) and various Arabic dialects. It also emphasizes alignment with Islamic values and Arab cultures, which may contribute to its superior factual grounding in Arabic content generation. jais-adapted-70b, a bilingual English-Arabic model adapted from Llama-2 (Touvron et al., 2023) , follows closely with a MedScore of 91.9%. Its strong Arabic proficiency, stemming from training on a massive high quality dataset of Arabic text, enables it to perform robustly despite being smaller than the large top-tier models.

LLaMA-3.3-70B-Instruct, a multilingual model that does not explicitly support Arabic, still achieves a moderate MedScore of 86.5%. While not optimized for Arabic nor the medical domain, its scale and general multilingual training allow for partial generalization to Arabic medical content, especially when compared to significantly smaller models.

BiMediX2-8B-hf, an English version of the BiMediX2 vision-language model built upon LLaMA-3.1 and trained on a large-scale bilingual and multimodal healthcare dataset, scores 76.8%, falling notably behind Fanar-9B despite being domain-specific. This suggests that while BiMediX2 benefits from domain alignment and bilingual pretraining, its multimodal architecture or reliance on the LLaMA-3.1 base may limit its factual accuracy in text-only generation tasks.

That said, BiMediX2-8B-hf demonstrates a significant improvement over its base model, LLaMA-3.1-8B-Instruct, which scores the lowest MedScore of 50.5%. This improvement highlights the value of task-specific fine-tuning on curated English-Arabic medical datasets. Although both are small models (8B), the contrast between them underscores the importance of domain adaptation, even within the same architecture family.

Turning to the OpenFactCheck results, we observe a consistent ranking pattern, though absolute scores are generally lower due to its binary scoring nature. Qwen2.5-Max again leads with 94.2%, followed by GPT-4o (90.1%), o1 (89.0%), and Deepseek-R1 (85.7%). Among smaller and medium models, Fanar (81.3%) and jais-adapted-70b (82.8%) retain strong performance, with the rest of the models exhibiting a gradual decline, culminating with Llama-3.1-8B-Instruct at 40.9%.

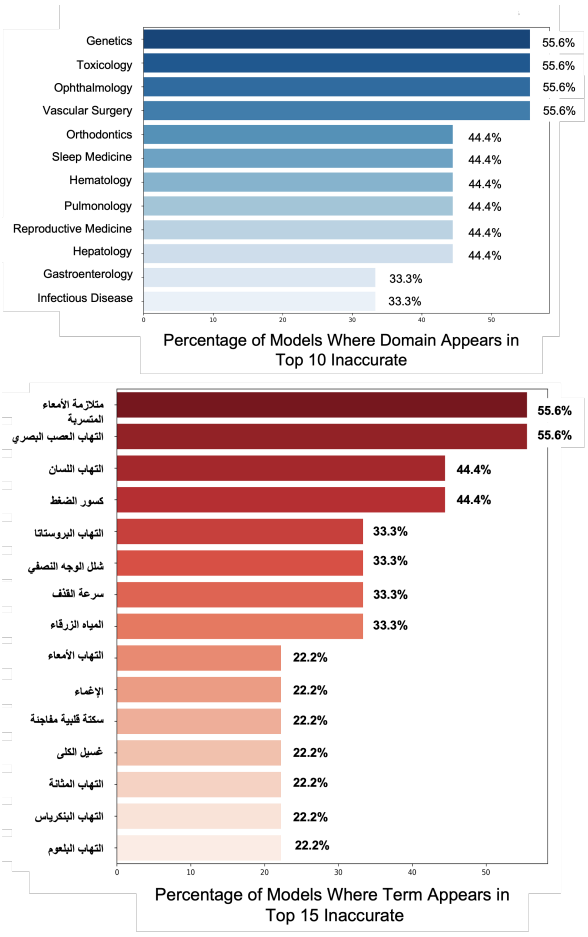

Figure 6: Aggregated analysis of common inaccuracies across all evaluated models. Top: highlights the medical domains that most frequently appear in the top inaccuracy lists across the nine models. Bottom: presents the most commonly occurring inaccurate medical terms in the generated content. These visualizations reveal consistent failure patterns that can inform future targeted model enhancements.

4.3 Cross-Model Failures in Medical Terms and Domains

While the previous analyses focus on model-specific performance, a cross-model investigation reveals consistent patterns of failure shared by multiple LLMs, particularly with respect to certain medical terms and domains. For each model, we analyzed the 1,000 generated Arabic medical facts to identify the top 10 domains and top 15 medical terms with the highest inaccuracy rates. We then aggregated these findings across all nine models, yielding insights from a total of 9,000 generated samples. The individual failure patterns for each model are presented in Figure 7, Figure 8, and Figure 9 in Appendix A, while the cross-model aggregation is summarized in Figure 6. These recurring inaccuracies suggest that certain medical concepts are systematically misrepresented, highlighting persistent challenges in Arabic medical understanding across current LLMs, regardless of model architecture or training approach.

Recurring Inaccurate Medical Terms. Among the most frequently misrepresented medical terms, leaky gut syndrome and optic neuritis stood out, appearing in the top inaccurate outputs of 5 out of 9 models (55.6%). Other recurring terms include glossitis, compression fractures, and prostatitis, which appeared in the top inaccurate terms of 3–4 models. Notably, even state-of-the-art models like GPT-4o and Qwen2.5-Max contributed to these inaccuracies, reinforcing the notion that term-specific challenges are systemic rather than isolated.

Many of these terms reflect complex or less commonly encountered medical conditions, which may suffer from limited representation in Arabic-language medical corpora. Additionally, the morphological and syntactic complexity of Arabic may compound the difficulty in modeling precise clinical terms, leading to hallucinations or vague outputs in these areas.

Challenging Medical Domains. At the domain level, Genetics, Toxicology, Ophthalmology, and Vascular Surgery were the most frequently observed failure categories, each appearing in the top inaccurate domains of 5 models (55.6%). Close behind were Orthodontics, Sleep Medicine, Hematology, and Pulmonology, each flagged by 4 models. These domains often involve technical terminology, rapidly evolving research, and nuanced clinical context, making accurate generation especially challenging.

We hypothesize that these domain-level failures arise from two key factors: (1) data scarcity in high-quality Arabic medical texts for these domains, and (2) the models' inability to generalize reliably across specialized areas without explicit domain adaptation or retrieval-based augmentation.

4.4 Finer-Grained Hallucination Categories

While our quantitative evaluation highlights which domains and terms are most prone to hallucination, a finer-grained manual analysis reveals the qualitative nature of these errors. We manually reviewed a subset of factually incorrect instances and identified several recurring hallucination categories. These categories capture different ways

in which LLMs deviate from factual accuracy in Arabic medical factual generation, ranging from clinical errors to linguistic artifacts.

The most prominent were clinical hallucinations, where models produced inaccurate medical facts, misdiagnoses, or misleading claims. We also observed statistical hallucinations, characterized by unverifiable or over-claimed prevalence and efficacy rates presented with false precision. A third category, linguistic hallucinations, reflected vulnerabilities in Arabic processing, including phonetic confusions, mistranslations, and the invention of non-existent medical terms. In addition, temporal hallucinations arose from outdated medical statistics or obsolete recommendations, while cultural/geographic hallucinations stemmed from globally overgeneralized claims that failed to capture regional and cultural variation in health practices. Together, these categories highlight both well-known LLM failure modes and Arabic-specific vulnerabilities, such as phonetic artifacts and culturally misaligned assumptions. Figure 10 in Appendix B provides a representative instance for each hallucination category from the *MedHalwasa* dataset, where each example is accompanied by a justification explaining both why the claim is factually incorrect and why it belongs to its respective hallucination category.

5 Conclusion

In this work, we present *MedHalwasa*, the first comprehensive dataset generated for evaluating hallucinations in Arabic medical fact generation. Recognizing the critical implications of factual errors in clinical contexts, our study systematically examines the reliability of nine prominent large language models by generating and analyzing 9,000 factual Arabic medical statements across 35 medical domains. We propose a scalable and reproducible framework for data generation and automatic factual annotation, enabling consistent evaluation across models. Our dual metric approach, using both domain-specific and domain-agnostic evaluators, provides a nuanced understanding of model performance.

Through detailed analyses, we observe notable disparities in factual accuracy across model scales and configurations. Large-scale LLMs consistently outperform smaller and medium-sized models in Arabic medical fact generation, underscoring the impact of scale on factual reliability. Among the smaller and medium-scale models, those trained on high-quality Arabic corpora demonstrate stronger performance compared to general-purpose counterparts. Additionally, domain specialization plays a significant role, where a medically tuned model shows clear improvements over its base, general-purpose variant. Our cross-model examination also uncovers recurring inaccuracies tied to specific medical terms and domains, suggesting deeper limitations in current LLMs' medical reasoning and Arabic linguistic understanding, irrespective of model architecture.

MedHalwasa contributes not only a novel dataset but also key empirical insights into the nature of hallucinations in Arabic medical generation. These findings carry important implications for the deployment of LLMs in real-world healthcare applications, particularly in low-resource languages like Arabic. We hope our work serves as a foundation for future efforts aiming to build more trustworthy, medically grounded, and linguistically aware LLMs. Researchers interested in rare diseases or specialized subdomains can readily build upon our methodology to expand the vocabulary and conduct targeted investigations.

6 Limitations

In our data generation process, we employed a single, unified prompt for all models to ensure a fair and unbiased comparison. However, LLMs may respond differently to varied phrasings, and certain prompts could better align with specific models' training distributions. This fixed prompting strategy may not reveal the upper bound of each model's capabilities, especially in prompt-sensitive scenarios. Future work could explore prompt engineering or model-specific prompting to better characterize factual performance under optimal conditions.

Additionally, our study primarily emphasizes medical factual accuracy and does not comprehensively evaluate the linguistic fluency, coherence, or dialectal correctness of the generated Arabic text. These factors, while orthogonal to factuality, are critical for the practical adoption of LLMs in real-world Arabic healthcare applications and deserve future exploration.

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A Appendix: Detailed breakdown of domain and term-level inaccuracies

B Appendix: Finer-grained hallucination categories with representative Arabic examples and justifications.

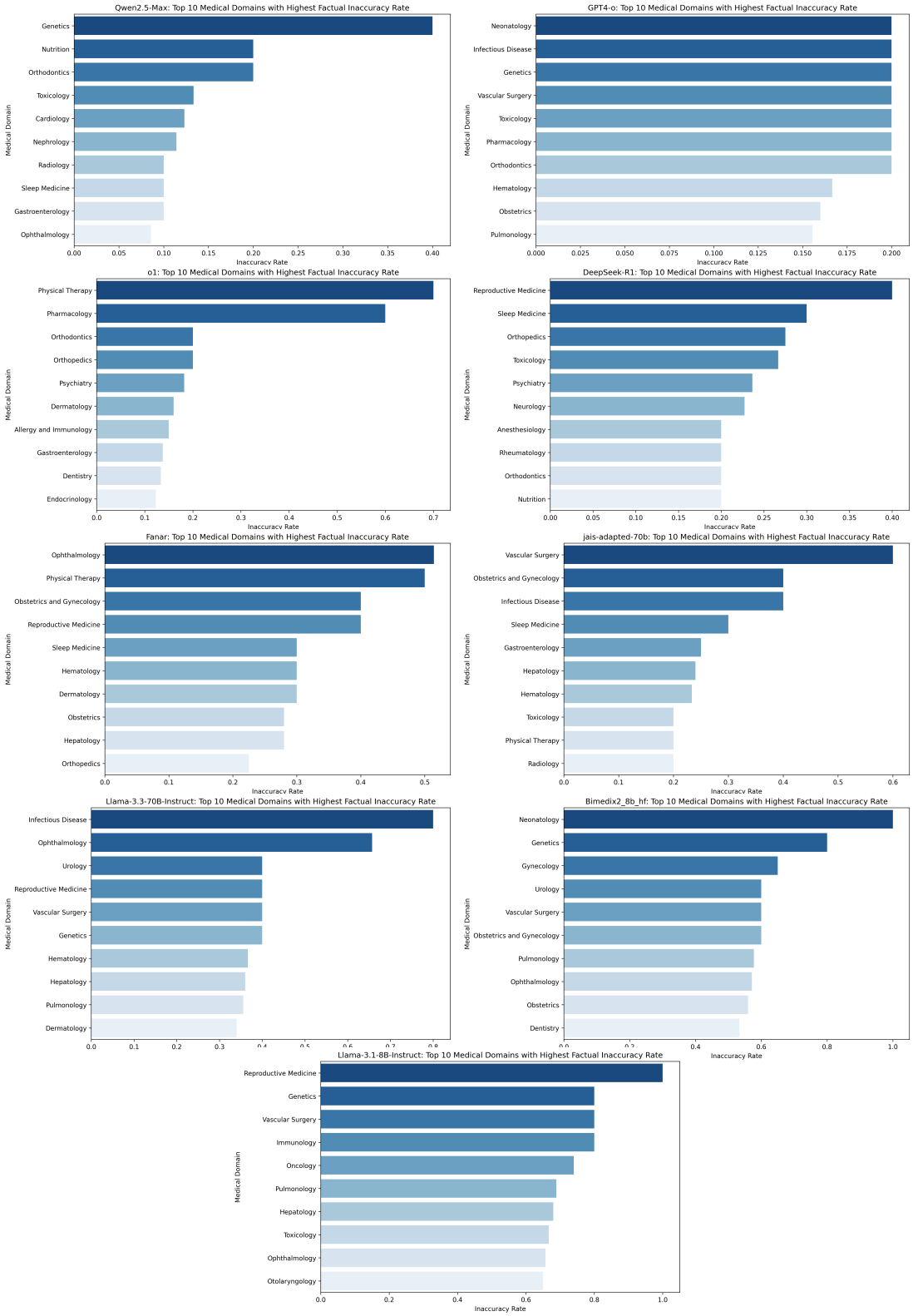

Figure 7: Top 10 medical domains with the highest inaccuracy rates in the generated content across the nine evaluated models.

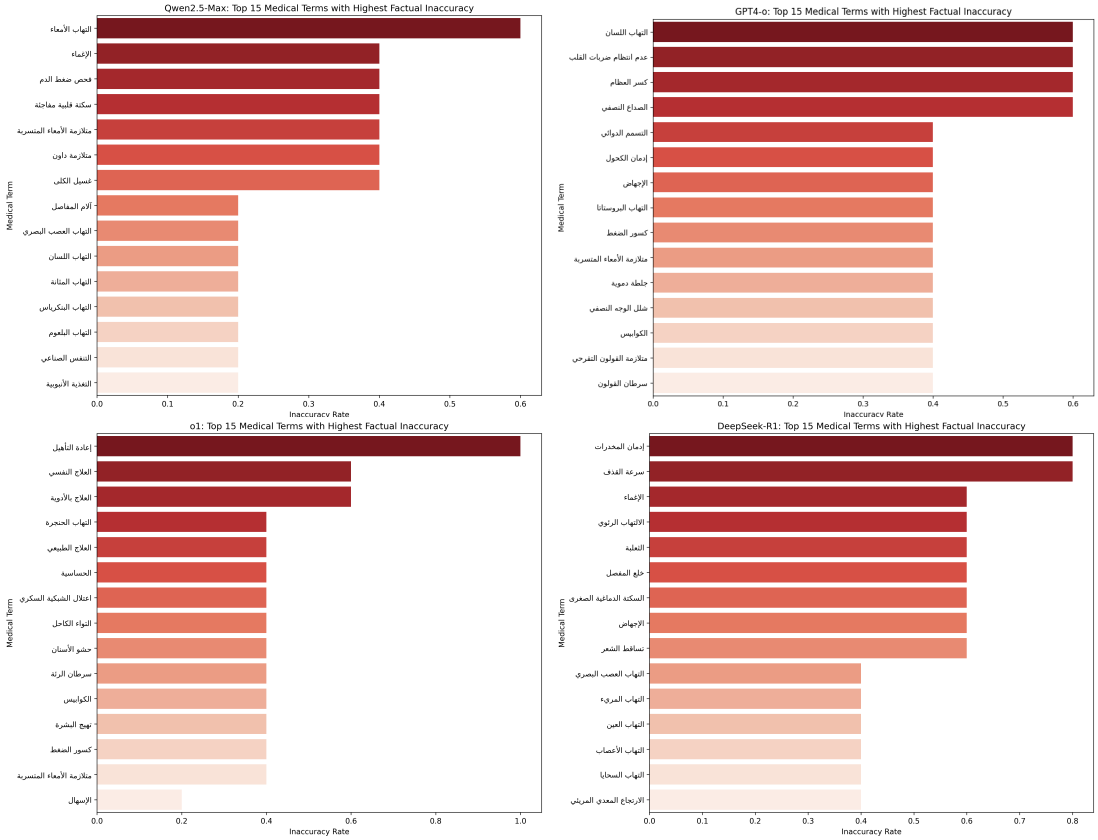

Figure 8: Top 15 medical terms with the highest inaccuracy rates in the generated content across the four large evaluated models.

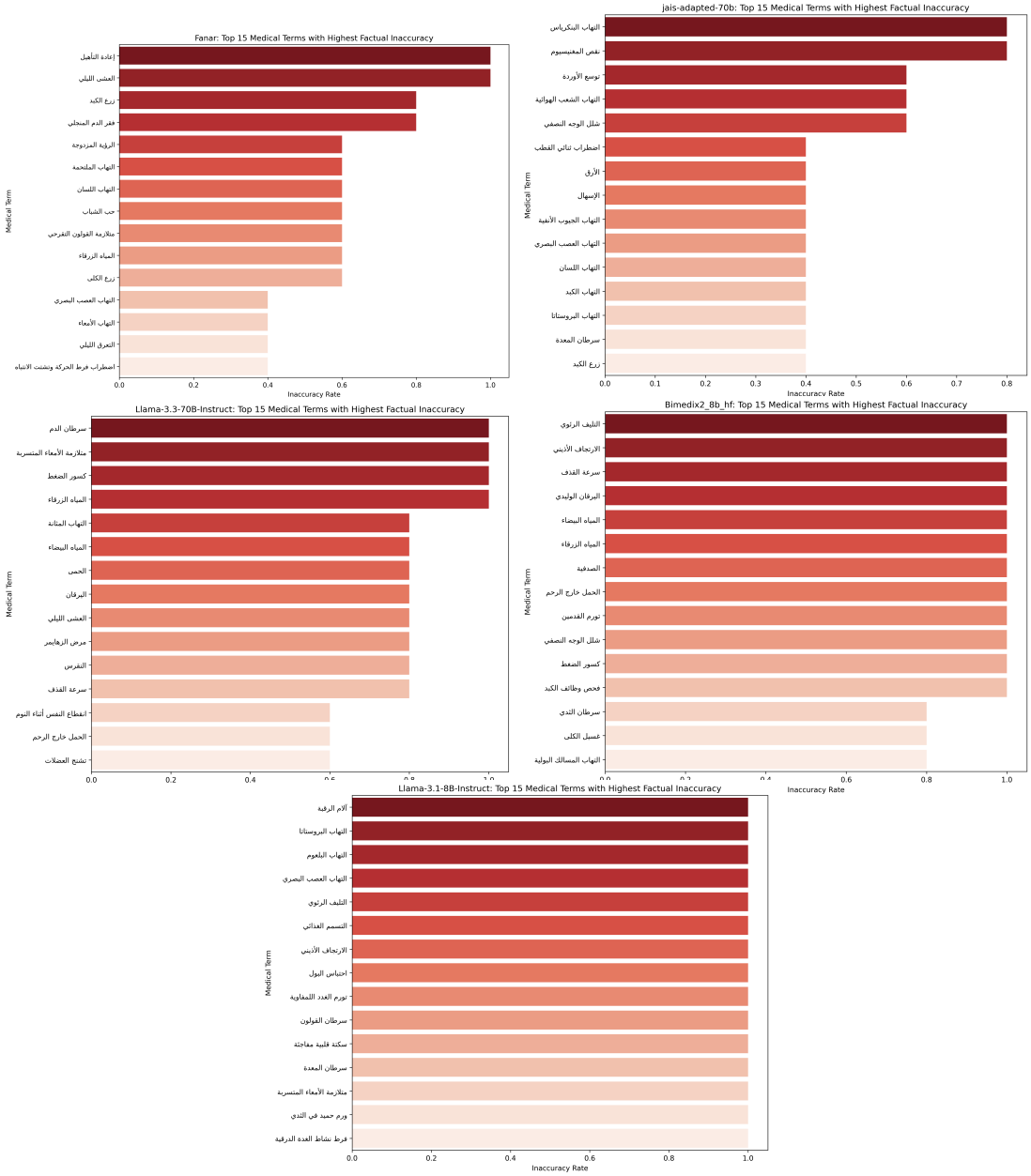

Figure 9: Top 15 medical terms with the highest inaccuracy rates in the generated content across the five medium/small evaluated models.

Category	Arabic Sample	Justification
Clinical Hallucination (incorrect medical facts, advice, or diagnoses)	يمكن أن يتسبب الالتهاب الحاد في العين، المعروف أيضًا باسم التهاب القرنية أو القزحية، في الشعور بالألم الشديد وعدم الراحة عند التعرض للضوء "Acute eye inflammation, also known as keratitis or iritis, can cause severe pain and discomfort when exposed to light"	This incorrectly conflates three distinct conditions. (التهاب العين-eye inflammation) (التهاب القرنية-keratitis) and (التهاب القزحية-iritis) which are specific inflammations of different parts of the eye (cornea vs. iris) with different causes and treatments. They are not synonyms.
Temporal Hallucination (outdated dates or statistics)	وفقاً لمنظمة الصحة العالمية، تعد السكتة الدماغية السبب الخامس الرئيسي للوفاة ورابع أكثر حالات الإعاقة انتشاراً حول العالم "According to the World Health Organization, stroke is the fifth leading cause of death and the fourth most common cause of disability worldwide."	As of recent WHO reports (e.g., World Health Statistics 2024), stroke is the 3rd leading cause of death globally. Ranking it as 5th is outdated information.
Cultural/Geographic Hallucination (false assumptions tied to culture or region)	تُعد الفول السوداني ومنتجات الصويا من أكثر المسببات الغذائية شيوعاً للحساسية لدى الأطفال والمراهقين حول العالم "Peanuts and soy products are the most common food allergens in children and adolescents worldwide."	This is geographically inaccurate. While peanut allergy is common in Western countries (e.g., US, UK), it is significantly less common in many parts of Asia and the Middle East. Soy allergy is also not among the *most* common globally. Common allergens vary greatly by region (e.g., sesame, shellfish are top allergens in some areas). This statement makes a false global assumption.
Statistical Hallucination (unverifiable or overclaimed statistics)	يزيد مرض السكري من خطر الإصابة بأمراض القلب والأوعية الدموية، حيث يؤثر على نحو 64% من المصابين بالسكري في العالم العربي "Diabetes increases the risk of cardiovascular disease, affecting about 64% of diabetic patients in the Arab world."	The first clause is correct. The second clause presents a specific, unverifiable, and likely invented statistic ("64%"). This is a classic LLM overclaim of a precise number without a source.
Linguistic Hallucination (phonetic confusions, mistranslations, or invented terms)	يمكن أن يتأثر ظهور حب الشباب بعوامل مختلفة مثل التغيرات الهرمونية، خاصة خلال فترة المراهقة، بالإضافة إلى استخدام بعض الأدوية وبعض الأطعمة الغنية بالإندوجينيز "The appearance of acne can be influenced by various factors such as hormonal changes, especially during adolescence, as well as the use of certain medications and some foods rich in بالإندوجينيز."	"الإندوجينيز"is an invented term in this context. The intended word is likely (الاندروجينات-androgens), the hormones that stimulate oil production. This is a linguistic error, likely from mistranslation or phonetic confusion.

Figure 10: The most commonly occurring hallucination categories identified in the MedHalwasa dataset, with one representative Arabic sample and its justification. The justification explains both why the instance is factually incorrect and why it belongs to its respective hallucination category. Incorrect elements in the Arabic samples are highlighted in red.