

Exploring the Role of Knowledge Graph-Based RAG in Japanese Medical Question Answering with Small-Scale LLMs

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Abstract

Large language models (LLMs) perform well in medical QA, but their effectiveness in Japanese contexts is limited due to privacy constraints that prevent the use of commercial models like GPT-4 in clinical settings. As a result, recent efforts focus on instruction-tuning open-source LLMs, though the potential of combining them with retrieval-augmented generation (RAG) remains underexplored. To bridge this gap, we are the first to explore a knowledge graph-based (KG) RAG framework for Japanese medical QA small-scale open-source LLMs. Experimental results show that KG-based RAG has only a limited impact on Japanese medical QA using small-scale open-source LLMs. Further case studies reveal that the effectiveness of the RAG is sensitive to the quality and relevance of the external retrieved content. These findings offer valuable insights into the challenges and potential of applying RAG in Japanese medical QA, while also serving as a reference for other low-resource languages.

Keywords

Japanese Medical Question Answering, Retrieval-Augmented Generation, Small-Scale LLMs, Knowledge Graph

1. Introduction

Large language models (LLMs) have achieved remarkable performance in medical question answering (QA), even demonstrating the ability to pass medical licensing exams (e.g., the United States Medical Licensing Examination, USMLE) [1], which highlights their potential to understand complex medical knowledge. In particular, recent research [2, 3, 4] has explored the use of retrieval-augmented generation (RAG) [5] to incorporate external medical knowledge into LLMs, effectively mitigating “hallucination” issues [6, 7, 8, 9] and further enhancing their applicability in medical QA tasks.

While these advances are promising, most existing efforts [10, 11] focus on English-only scenarios, with limited exploration of multilingual medical QA, particularly in Japanese. Since mainstream LLMs [12, 13] are predominantly trained on English-centric medical data, the significant imbalance in resource distribution [14] limits their effectiveness in Japanese medical QA scenarios. While GPT-4 has demonstrated strong performance on the Japanese NMLE [15], strict privacy regulations prevent its use in clinical settings. As a result, research has shifted toward open-source LLMs, but progress is hindered by the scarcity of high-quality Japanese medical data—highlighting the broader challenges faced by low-resource languages.

To address this limitation, in this paper, we are the first to explore the use of Knowledge Graph-based RAG for Japanese medical question answering, specifically targeting small-scale LLMs. Given the limited accessibility of external Japanese medical resources, we use the easily accessible external medical

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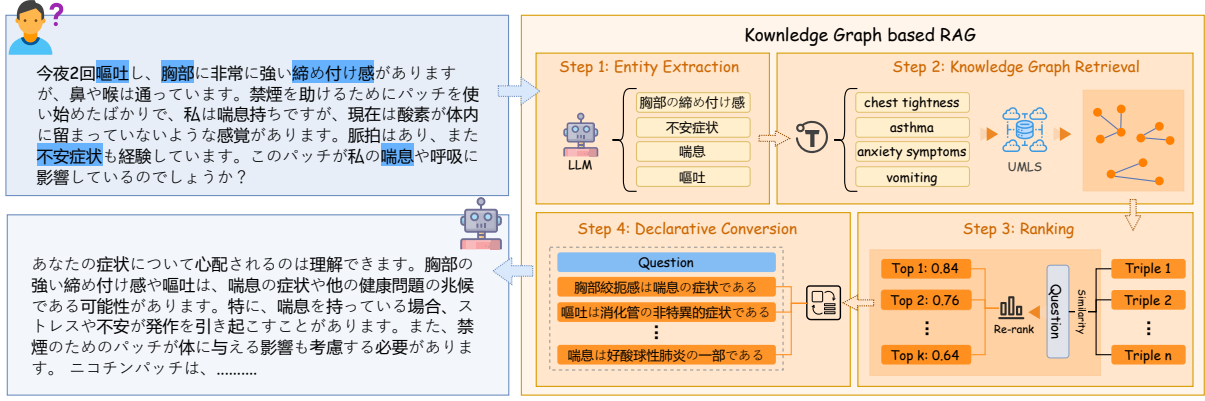


Figure 1: The pipeline of our knowledge graph-based RAG mechanism. Given a Japanese medical question, relevant medical knowledge is retrieved from the external knowledge base and combined with the original Japanese question as input to the LLM for answer generation. The English translation and full content are provided in Appendix A.

knowledge base UMLS [16] to support knowledge retrieval, following the design of MKG-Rank [17]. By applying word-level translation, LLMs can integrate non-Japanese-centric medical knowledge, mitigating the limitations caused by the relative scarcity of Japanese medical data and its access restrictions. Empirical results show that the KG-based RAG has limited effect on Japanese medical QA with small open-source LLMs, largely depending on the quality and relevance of the retrieved KGs from external knowledge bases.

2. Method

2.1. Base Models

Our work focuses on evaluating the performance of small-scale LLMs in Japanese medical QA. Specifically, we select: (1) models with fewer than 5B parameters, including Borea-Phi-3.5-Mini-Instruct-Common [18] and LLaMA-3-ELYZA-JP-8B [19]; (2) models with 5B-10B parameters, including LLM-JP-3-7.2B-Instruct3 [20], Mistral-7B-Instruct-v0.3 [21], Qwen2.5-7B-Instruct [22], and LLaMA-3.1-8B-Instruct [23]; and (3) 10B-32B models, including Qwen2.5-14B-Instruct [24], Phi-4-14B [25], and Gemma-3-12B-it [26]. In addition, we evaluate the commercial LLM GPT-4o-mini [27] as a proprietary baseline.

2.2. Knowledge Graph-based RAG

Our pipeline, as illustrated in Fig. 1, consists of four main steps: (1) Given a medical question Q , we first use an LLM to extract relevant medical entities \mathcal{E} ; (2) The extracted entities \mathcal{E} are translated into English via word-level translation and used to query external medical knowledge base UMLS to obtain relevant KGs \mathcal{G} . (3) A ranking mechanism is applied to select the most relevant triples \mathcal{G}' based on their semantic relevance to the question Q ; (4) The selected triples are then converted into declarative sentences by an LLM, along with the original question, are provided as input to the LLM for answer generation.

Prompts. We provide the prompts used in our knowledge graph-based RAG mechanism, including Medical Entity Extraction, Declarative Conversion and Answer Generation.

3. Experiment

3.1. Datasets

We selected three long-form medical question answering datasets: ExpertQA-Bio, ExpertQA-Med, and LiveQA. ExpertQA is a high-quality QA dataset verified by domain experts, from which we used 96 bio-

Medical Entity Extraction
text: {question}
Please extract at most 4 terms related to medical that you think are the most important from the provided text. Returns the result in the following json form. All the results are merged into one json.
-- Examples of results:
{"medical terminologies": ["term1", "term2", ...]}
result:

Table 1
Prompt Used for Medical Entity Extraction.

logical questions (ExpertQA-Bio) and 504 medical questions (ExpertQA-Med) [28]. LiveQA consists of consumer health questions submitted to the National Library of Medicine, comprising 627 training QA pairs and 104 test pairs [29]. All datasets were originally in English and were translated into Japanese using a multi-stage agentic machine translation framework [30]. We provide detailed statistics of the evaluation datasets, including the number of samples and the average word count of questions and answers, as shown in Table 2.

Dataset	Size	Question Length	Answer Length
ExpertQA-Bio	96	56.7	410.7
ExpertQA-Med	504	56.0	378.1
LiveQA	627	118.9	438.3

Table 2
Statistics of the evaluation datasets.

3.2. Metrics

We adopt ROUGE-L [31] and BERTScore [32] to evaluate the quality of answers generated by LLMs for Japanese medical QA tasks. These metrics provide a comprehensive assessment of both lexical and semantic accuracy.

3.3. Results and Analysis

Table 3 presents the performance comparison between KG-based RAG and the baseline LLMs on the medical QA task. In general, the results suggest that the impact of our RAG mechanism is relatively limited, with performance fluctuations observed across different base models. Specifically, for Borea-Phi-3.5, LLaMA-3-ELYZA-JP-8B, Qwen2.5-14B, Gemma-3-12B-it, and GPT-4o-mini, the RAG leads to marginal changes, with performance fluctuating within 1% compared to the respective base models. In contrast, Qwen2.5-7B and Phi-4-14B exhibit overall improvements when enhanced with RAG, particularly Phi-4-14B, which achieves improvements of up to +4.78% in ROUGE-L and +4.01% in BERTScore. On the other hand, the RAG leads to negative impacts on Mistral-7B and LLaMA-3.1-8B, resulting in performance degradation.

3.4. Case Study

To further investigate the reasons behind the relatively limited impact of RAG, we analyze the intermediate reasoning process, as shown in Table 4. Specifically, in Case 1 (top), the retrieved medical knowledge includes the information that is relevant and helpful for answering the question (e.g. “ワルファリンは生理的に凝固因子濃度を低下させる効果がある”). However, we observe that

Model	ExpertQA-Bio		ExpertQA-Med		LiveQA	
	ROUGE-L	BERTScore	ROUGE-L	BERTScore	ROUGE-L	BERTScore
Borea-Phi-3.5 [18]	4.33	61.20	4.92	51.54	4.05	59.98
Borea-Phi-3.5 + RAG	4.77 (+0.44%)	61.32 (+0.12%)	4.82 (-0.10%)	61.39 (-0.15%)	3.97 (-0.08%)	59.71 (-0.28%)
LLaMA-3-ELYZA-JP-8B [19]	22.29	76.51	23.12	76.81	16.23	71.51
LLaMA-3-ELYZA-JP-8B + RAG	22.53 (+0.24%)	76.22 (-0.29%)	23.13 (+0.01%)	76.75 (-0.06%)	16.37 (+0.14%)	71.56 (+0.05%)
Mistral-7B [21]	20.85	75.25	20.21	74.67	15.70	70.99
Mistral-7B + RAG	17.39 (-3.46%)	72.13 (-3.12%)	17.59 (-2.62%)	72.35 (-2.32%)	13.76 (-1.94%)	69.15 (-1.84%)
Qwen2.5-7B [22]	19.09	75.15	19.52	75.39	14.60	70.88
Qwen2.5-7B + RAG	20.15 (+1.06%)	75.18 (+0.03%)	20.56 (+1.04%)	74.95 (-0.44%)	15.97 (+1.37%)	71.68 (+0.80%)
LLaMA-3.1-8B [23]	18.84	74.09	18.49	74.42	14.78	70.50
LLaMA-3.1-8B + RAG	18.01 (-0.83%)	72.04 (-2.05%)	18.01 (-0.48%)	72.40 (-2.02%)	14.43 (-0.35%)	69.30 (-1.20%)
Qwen2.5-14B [24]	17.00	71.92	17.01	71.44	13.85	68.63
Qwen2.5-14B + RAG	17.19 (+0.19%)	71.25 (-0.67%)	17.47 (+0.46%)	71.74 (+0.30%)	13.89 (+0.04%)	68.62 (-0.01%)
Phi-4-14B [25]	9.72	65.89	9.15	65.12	8.78	64.97
Phi-4-14B + RAG	12.18 (+2.46%)	67.38 (+1.49%)	13.93 (+4.78%)	69.13 (+4.01%)	11.18 (+2.40%)	66.75 (+1.78%)
Gemma-3-12B-it [26]	19.79	74.65	21.25	74.89	14.61	69.71
Gemma-3-12B-it + RAG	20.44 (+0.65%)	75.13 (+0.48%)	21.99 (+0.74%)	75.71 (+0.82%)	15.34 (+0.73%)	70.42 (+0.71%)
GPT-4o-mini [27]	24.92	77.67	26.78	78.67	17.94	73.25
GPT-4o-mini + RAG	24.41 (-0.51%)	77.45 (-0.22%)	26.20 (-0.58%)	78.53 (-0.14%)	17.85 (-0.09%)	73.28 (+0.03%)

Table 3

Evaluation of ROUGE-L and BERTScore for base models and their KG-based RAG-enhanced variants on three medical QA datasets: ExpertQA-Bio, ExpertQA-Med, and LiveQA.

<p>Question: ワルファリン (ワーファリン) を服用している人は避けるべき野菜は何ですか? (Which vegetables should people taking warfarin (Coumadin) avoid?)</p> <p>Retrieved Medical Knowledge: 1. ワルファリンは生理的に凝固因子濃度を低下させる効果がある。(Warfarin physiologically reduces the concentration of coagulation factors.) 2. ワルファリンはクマリン系の抗凝固薬である。(Warfarin is a coumarin-based anticoagulant.) ...</p> <p>Ground Truth: ワーファリンを服用している人は、ビタミン K を多く含む野菜の摂取を避けるか制限する必要があります。なぜなら、それが薬の血液凝固抑制効果（血液をサラサラにする効果）を妨げる可能性があるからです。...(People taking warfarin should avoid or limit the intake of vegetables that are high in vitamin K, as it may interfere with the medication's blood clotting inhibition effect (the effect of making the blood thinner).)</p> <p>Generated Answer: ワルファリンを服用している人が避けるべき野菜は、特にビタミン K を多く含むものです。ビタミン K は血液凝固に関与しており、ワルファリンの効果を減少させる可能性があります。...(People taking warfarin should avoid vegetables that are particularly high in vitamin K. Vitamin K is involved in blood clotting and may reduce the effectiveness of warfarin.)</p>
<p>Question: 抗生薬は通常、細菌感染または真菌感染のある患者に投与されます。ウイルスが原因であることが多い疾患については、はどうでしょうか? (Antibiotics are typically administered to patients with bacterial or fungal infections. But what about diseases that are often caused by viruses?)</p> <p>Retrieved Medical Knowledge: 1. バイ菌感染は、他のバイ菌性疾患に分類されます。(Bacterial infections are classified under other bacterial diseases.) 2. バイ菌感染は、肝臓に分類されます。(Bacterial infections are classified as liver abscesses.) ...</p> <p>Ground Truth: 抗生物質は、感冒、インフルエンザ、様々な咳などのウイルス感染症に対しては効果がありません。...これは、ウイルスが細胞ではなく、細菌細胞と比較して細胞壁を持たないためです。...(Antibiotics are ineffective against viral infections such as the common cold, influenza, and various types of cough. ...This is because viruses do not have a cell wall, unlike bacterial cells. ...)</p> <p>Generated Answer: 抗生物質は主に細菌感染に対して効果がありますが、ウイルス感染に対しては効果がありません。ウイルスが原因の疾患、例えばインフルエンザや風邪などには、抗生物質は無効です。...(Antibiotics are mainly effective against bacterial infections but are ineffective against viral infections. For illnesses caused by viruses, influenza or the common cold, antibiotics do not work.)</p>

Table 4

Case Study. Two cases are presented, with full content and English translations provided in Appendix B.

most LLMs already possess this knowledge internally, which explains why RAG offers only marginal improvements in such cases. On the other hand, for Case 2 (bottom), the retrieved medical knowledge does not help answer the question (e.g. “バイ菌感染は、肝臓に分類されます”). This is primarily because the specialized biomedical concepts in UMLS may not align well with broader, more general medical questions. Consequently, the retrieved information provides limited assistance and may even introduce noise that negatively impacts the LLM’s reasoning.

4. Conclusion

This work presents the first exploration of a knowledge graph-based RAG framework for Japanese medical QA using small-scale open-source LLMs. Empirical findings show that its overall impact is limited, primarily constrained by the quality and relevance of the retrieved content. These insights highlight the challenges and potential of applying RAG to Japanese and other low-resource language medical QA tasks.

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Declaration on Generative AI

In this work, the first author, Yingjian Chen, used ChatGPT and Grammarly in order to: Grammar and spelling check, sentence polishing. After using these tools, Yingjian Chen reviewed and edited the content as needed and takes full responsibility for the publication's content.

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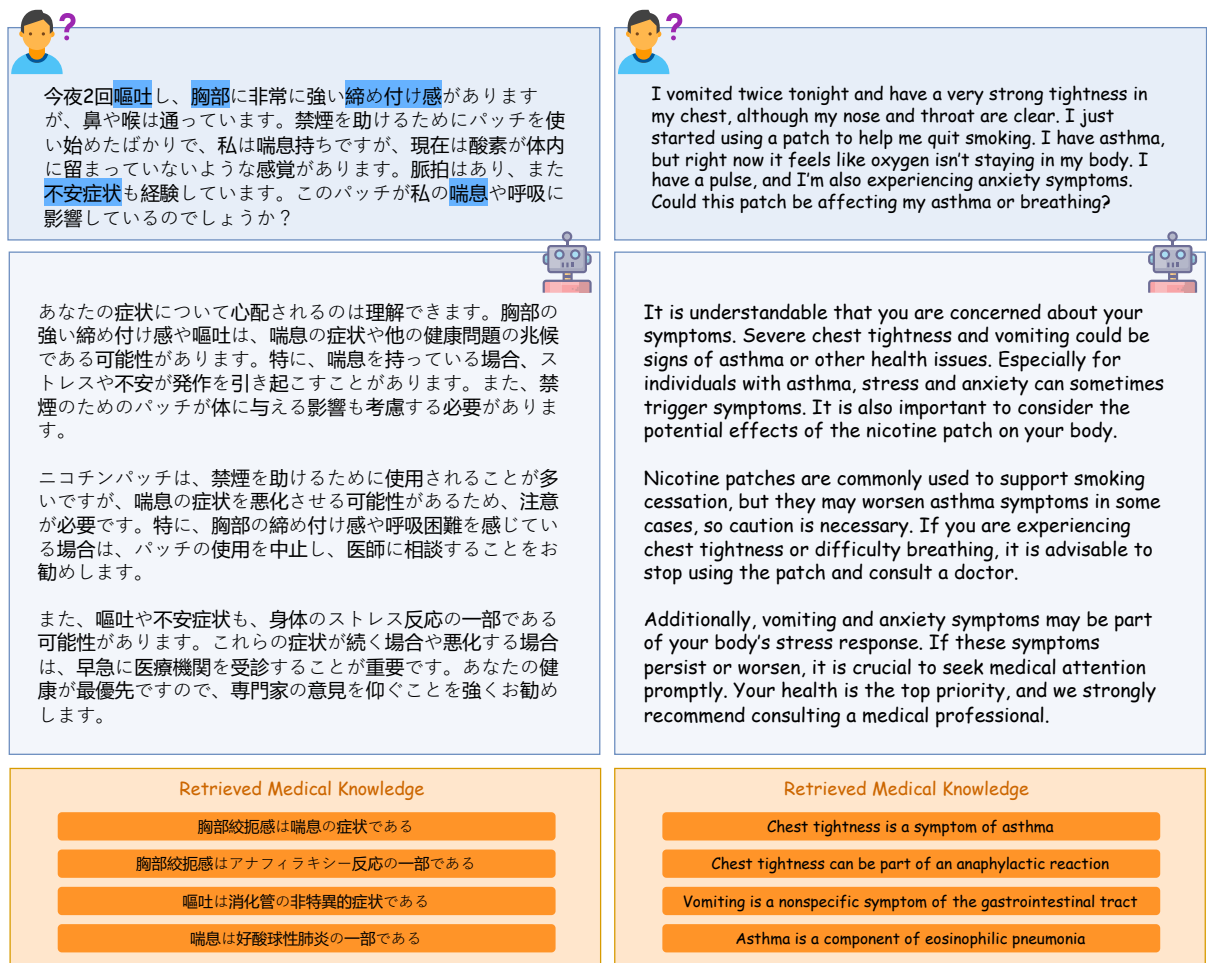


Figure 2: English translation and the full content of the question and answer in the Fig. 1

A. English Translation of the Content in Fig. 1

For clearer presentation, we provide the English translation and the full content of the question and answer in the Fig. 1, as illustrated in Fig. 2.

Declarative Conversion
<p>あなたは医学分野の知能助手です。</p> <p>すべての背景知識をそれぞれ日本語の平叙文に変換する。医学に関係ないと思うものは何でも削除できます。</p> <p>- Background Knowledge: {triple}</p> <p>Converted Background Knowledge:</p>

Table 5
Prompt Used for Declarative Conversion.

B. Case Study Details

For clarity and ease of understanding, we provide the full content and English translations of the cases from Table 4 here, as shown in Fig. 3 and Fig. 4.

Answer Generation with Medical Knowledge

あなたは医学分野の知能助手です。質問をよく分析し、提供された背景知識とあなた自身の知識に基づいて以下の質問に答えてください。できるだけ 512 の token 内で完全に回答します。日本語で質問に答える。

- 問題: {question}
- 背景知識: {background_knowledge}

- 答える:

Table 6

Prompt Used for Answer Generation with Medical Knowledge.

Case 1	
<p>Question:</p> <p>ワルファリン（ワーファリン）を服用している人は避けるべき野菜は何ですか？</p> <p>Which vegetables should people taking warfarin (Coumadin) avoid?</p>	<p>Retrieved Medical Knowledge:</p> <ol style="list-style-type: none">ワルファリンは生理的に凝固因子濃度を低下させる効果がある。 Warfarin physiologically reduces the concentration of coagulation factors.ワルファリンは生理的に凝固因子活性を低下させる効果がある。 Warfarin has the effect of lowering the activity of coagulation factors physiologically.ワルファリンはクマリン系の抗凝固薬である。 Warfarin is a coumarin-based anticoagulant.ワルファリンは WARFARIN SODIUM 3 mg 経口錠剤の有効成分である。 Warfarin is the active ingredient in WARFARIN SODIUM 3 mg oral tablets.
<p>Ground Truth:</p> <p>ワーファリンを服用している人は、ビタミンKを多く含む野菜の摂取を避けるか制限する必要があります。なぜなら、それが薬の血液凝固抑制効果（血液をサラサラにする効果）を妨げる可能性があるからです。避けるか適度に摂取すべき野菜には、ケール、ほうれん草、コラードグリーン（ケールに似た葉野菜）、フダンソウ（スイスチャード）、カラシナ（からし菜）、ビートの葉、かぶの葉、ブロッコリーなどの葉物野菜が含まれます。さらに、パセリやコリアンダー（パクチー）などのハーブもビタミンKを多く含むため、ワーファリン服用中は適度に摂取すべきです。</p> <p>People taking warfarin should avoid or limit the intake of vegetables rich in vitamin K, as they may interfere with the blood-thinning effect of the medication. Vegetables that should be avoided or consumed in moderation include kale, spinach, collard greens (leafy greens similar to kale), Swiss chard, mustard greens, beet greens, turnip greens, and broccoli. Additionally, herbs such as parsley and coriander (cilantro), which are also high in vitamin K, should be consumed in moderation while taking warfarin.</p>	<p>Generated Answer:</p> <p>ワルファリンを服用している人が避けるべき野菜は、特にビタミンKを多く含むものです。ビタミンKは血液凝固に関与しており、ワルファリンの効果を減少させる可能性があります。具体的には、以下のような野菜が挙げられます。</p> <p>－ ケール － ほうれん草 － ブロッコリー － キャベツ － パセリ</p> <p>これらの野菜はビタミンKの含有量が高いため、ワルファリンの効果を妨げる可能性があるため、摂取を控えるか、医師と相談の上で適切な量を守ることが重要です。</p> <p>People taking warfarin should avoid vegetables that are particularly high in vitamin K, as vitamin K is involved in blood clotting and may reduce the effectiveness of warfarin. Specifically, the following vegetables should be considered:</p> <p>－ Kale －Spinach －Broccoli －Cabbage －Parsley</p> <p>These vegetables contain high levels of vitamin K and may interfere with the effect of warfarin. It is important to either avoid them or consult with a doctor to ensure an appropriate amount is consumed.</p>

Figure 3: Full content and English translation of the case 1 in Table 4.

Case 2	
<p>Question:</p> <p>抗生薬は通常、細菌感染または真菌感染のある患者に投与されます。ウイルスが原因であることが多い疾患については、はどうでしょうか？</p> <p>Antibiotics are typically administered to patients with bacterial or fungal infections. But what about diseases that are often caused by viruses?</p>	<p>Retrieved Medical Knowledge:</p> <ol style="list-style-type: none"> 1. バイ菌感染は、ニトロフラン抗菌薬によって予防されることがあります。 2. バイ菌感染は、他のバイ菌性疾患に分類されます。 3. バイ菌感染は、肝膿瘍に分類されます。 4. バイ菌感染は、他のバイ菌感染に分類されます。 5. バイ菌感染は、ニトロフラン抗菌薬によって治療されることがあります。 <p>Bacterial infections may be prevented by nitrofurantoin antibiotics.</p> <p>Bacterial infections are classified under other bacterial diseases.</p> <p>Bacterial infections are classified as liver abscesses.</p> <p>Bacterial infections are classified as other bacterial infections.</p> <p>Bacterial infections may be treated with nitrofurantoin antibiotics.</p>
<p>Ground Truth:</p> <p>抗生物質は、感冒、インフルエンザ、様々な咳などのウイルス感染症に対しては効果がありません。ウイルス感染症の患者に対して、医師は症状管理のための一般用医薬品を含む治療を推奨することがあり、抗生物質を使用する場合は必要な場合にのみ使用することが常に推奨されます。場合によっては、HIVに対する抗ウイルス療法、インフルエンザ、COVID-19、サル痘 (mpox)、またはインフルエンザに対するオセルタミビルリン酸塩 (タミフル) など、特定のウイルスにのみ効果のある特定の薬剤が処方されることがあります。抗生物質は細菌感染症に特化して処方されるものであり、ウイルス感染症には効果がないことに注意することが重要です。これは、ウイルスが細胞ではなく、細菌細胞と比較して細胞壁を持たないためです。したがって、抗生物質はウイルス感染症に対して効果を示しません。</p> <p>Antibiotics are not effective against viral infections such as the common cold, influenza, and various types of coughs. For patients with viral infections, doctors may recommend treatments that include over-the-counter medications for symptom management, and antibiotics should only be used when necessary. In some cases, specific antiviral medications may be prescribed for certain viruses, such as antiretroviral therapy for HIV, oseltamivir phosphate (Tamiflu) for influenza, or treatments for COVID-19 or monkeypox (mpox). It is important to note that antibiotics are prescribed specifically for bacterial infections and are not effective for viral infections. This is because viruses do not have a cell wall, unlike bacterial cells. Therefore, antibiotics are ineffective against viral infections.</p>	<p>Generated Answer:</p> <p>抗生物質は主に細菌感染に対して効果がありますが、ウイルス感染に対しては効果がありません。ウイルスが原因の疾患、例えばインフルエンザや風邪などには、抗生物質は無効です。ウイルス感染に対しては、抗ウイルス薬が使用されることがあります。したがって、ウイルスが原因であることが多い疾患に対しては、抗生物質を投与することは適切ではありません。ウイルス感染に対しては、症状を緩和するための対症療法や、必要に応じて抗ウイルス薬が用いられます。</p> <p>Antibiotics are primarily effective against bacterial infections but are not effective against viral infections. For diseases caused by viruses, such as influenza and the common cold, antibiotics are ineffective. Antiviral medications may be used for viral infections. Therefore, it is not appropriate to administer antibiotics for diseases that are often caused by viruses. For viral infections, symptomatic treatments are used to relieve symptoms, and antiviral medications may be used when necessary.</p>

Figure 4: Full content and English translation of the case 2 in Table 4.