# **KoSimpleQA: A Korean Factuality Benchmark with an Analysis of Reasoning LLMs**

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#### **Abstract**

We present Korean SimpleQA (KoSimpleQA), a benchmark for evaluating factuality in large language models (LLMs) with a focus on Korean cultural knowledge. KoSimpleQA is designed to be challenging yet easy to grade, consisting of 1,000 short, fact-seeking questions with unambiguous answers. We conduct a comprehensive evaluation across a diverse set of open-source LLMs of varying sizes that support Korean, and find that even the strongest model generates correct answer only 33.7% of the time, underscoring the challenging nature of KoSimpleOA. Notably, performance rankings on KoSimpleQA differ substantially from those on the English SimpleQA, highlighting the unique value of our dataset. Furthermore, our analysis of reasoning LLMs shows that engaging reasoning capabilities in the factual QA task can both help models better elicit their latent knowledge and improve their ability to abstain when uncertain. KoSimpleQA can be found at https://anonymous.4open. science/r/KoSimpleQA-62EB.

#### 1 Introduction

Large language models (LLMs) are increasingly deployed in applications that demand high factual reliability, ranging from information access to education and cultural content delivery. However, despite recent progress, LLMs still frequently generate factually incorrect outputs, a phenomenon widely known as *hallucination* (Banerjee et al., 2025). This has motivated the development of benchmarks that directly measure factual reliability, such as SimpleQA (Wei et al., 2024) and Chinese SimpleQA (He et al., 2024), which evaluate models on short, fact-seeking questions with unambiguous answers.

However, existing benchmarks primarily focus on English and Chinese, while no equivalent bench-

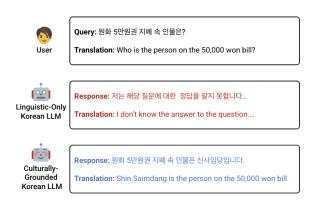


Figure 1: The importance of cultural knowledge for LLMs within a specific language community: an LLM with only linguistic competence responds fluently in Korean but fails, whereas one with Korean cultural knowledge correctly answers the question "Who is the person on the 50,000 won bill?"

mark exists for Korean. Simply translating existing benchmarks such as SimpleQA into Korean is not sufficient, since many of their questions are rooted in Anglophone cultural contexts and do not meaningfully assess models trained primarily on Korean data. Evaluating LLMs in a particular language requires not only linguistic competence but also an understanding of the cultural knowledge associated with that language community.

Figure 1 illustrates this distinction: a model with only linguistic competence can respond fluently in Korean but still fails on a culturally grounded question, whereas a model equipped with Korean cultural knowledge produces the correct answer. The release of Chinese SimpleQA further demonstrates that benchmarks need to be adapted to each language community's cultural context, rather than assuming a single benchmark can generalize across languages. In the same spirit, we propose **Korean SimpleQA** (**KoSimpleQA**), which fills this gap for Korean by providing a benchmark centered on Korean cultural knowledge.

Following the design principles of SimpleQA-

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style benchmarks, KoSimpleQA is challenging yet easy to grade, consisting of short, fact-seeking questions with unambiguous answers. We performed multiple rounds of human validation to control the quality of the dataset. We then systematically evaluated a broad range of open-source LLMs that support Korean, spanning different model families and parameter scales. Despite this diversity, no model generates correct answers more than 33.7% of the time, underscoring the difficulty of the benchmark. Moreover, performance rankings on KoSimpleQA diverge substantially from those on English SimpleQA, highlighting the distinct cultural dimension it captures.

In addition, we analyze the behavior of recent reasoning LLMs on KoSimpleQA. While reasoning has been emphasized as a core capability of frontier models, its role in factual QA has not been systematically examined. Our analysis shows that engaging reasoning capabilities can help models better elicit their latent knowledge and, importantly, make them more likely to abstain when uncertain. These findings suggest that reasoning not only reshapes how LLMs approach factuality but also provides new insights into the strengths and limitations of current models.

Our contributions are threefold:

- We release **Korean SimpleQA** (**KoSimpleQA**), the first benchmark targeting factuality in Korean cultural contexts.
- We provide a comprehensive evaluation across diverse LLMs, establishing new baselines and showing differences from English benchmarks.
- We additionally analyze reasoning models, offering preliminary insights into how reasoning affects factual reliability in factual QA tasks.

#### 2 KoSimpleQA

#### 2.1 Data Collection

We recruited annotators through two Korean crowd-sourcing platforms (Selectstar<sup>1</sup> and Flitto<sup>2</sup>). To build KoSimpleQA, we instructed annotators to create 1,000 knowledge-seeking questions to be used as the benchmark dataset under the following criteria.

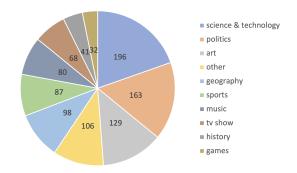


Figure 2: Distribution of categories in KoSimpleQA. The legend was ordered by sample size, from largest to smallest.

Category-guided annotation. We adopted the category distribution of SimpleQA as a reference and asked annotators to create questions within these predefined categories. By providing annotators with fixed categories in advance, we aimed to slightly reduce the cognitive burden of question creation, making the annotation process more efficient. Figure 2 illustrates the resulting category distribution.

**Cultural grounding.** All questions were required to reflect Korean cultural knowledge. For instance, questions about Korean literature, traditional holidays, or historical figures were encouraged.

**Temporal constraint.** To avoid questions tied to rapidly changing events, annotators were instructed to create items that could be answered with knowledge available up to December 31, 2023.

**Difficulty requirement.** Each question had to be sufficiently challenging such that at least one of the four strong closed-source LLMs we selected (HCX-005 (Yoo et al., 2024), gpt-4o-2024-05-13 (Hurst et al., 2024), gemini-2.0-flash<sup>3</sup>, and claude-3-5-sonnet-20240620<sup>4</sup>) failed to produce the correct answer. This criterion guaranteed that KoSimpleQA poses meaningful challenges even for current high-performing systems.

**Unambiguous answers.** Every question was required to admit exactly one short, unambiguous answer. This property was critical to ensuring both reliable grading and fairness across models, avoiding subjective judgments or multi-faceted answers.

https://selectstar.ai/

<sup>&</sup>lt;sup>2</sup>https://www.flitto.com/

<sup>3</sup>https://blog.google/
technology/google-deepmind/
google-gemini-ai-update-december-2024/
4https://www.anthropic.com/news/
claude-3-5-sonnet

**Source verification.** Annotators were instructed to record up to four reliable source links supporting each answer at the time of question creation. These references were later used during the quality control phase to verify factual accuracy and ensure reproducibility. By explicitly linking each answer to verifiable evidence, we reduced the likelihood of annotation errors and improved transparency in dataset construction.

#### 2.2 Quality Control

To ensure the quality and factual reliability of KoSimpleQA, we conducted a two-stage verification process. Because the dataset was constructed using two independent annotation platforms, data created on one platform were cross-validated by annotators from the other. In addition, an expert with experience in evaluating large language models manually inspected sampled questions, provided detailed feedback on problematic cases, and issued updated guidelines to the annotation platforms. The platforms then re-reviewed the entire dataset based on these revised instructions, completing the quality control cycle.

#### 2.3 Metrics

We follow the SimpleQA metrics using Correct (CO), Not Attempted (NA), Incorrect (IN), Correct Given Attempted (CGA), and F-score.

## 3 Experiments

#### 3.1 Setting

#### 3.1.1 Baselines

We evaluated a variety of open-source models with fewer than 70 billion parameters that are known to support the Korean language, categorizing them into two groups: **Korean Community LLMs** and **Multilingual LLMs Supporting Korean**.

- **Korean Community LLMs**: EXAONE 3.5 (Research et al., 2024), HyperCLOVA X (HCX) SEED<sup>5</sup>, and kanana 1.5<sup>6</sup>
- Multilingual LLMs Supporting Korean: gemma 3 (Team et al., 2025), Llama 3.1 (Dubey et al., 2024), and Qwen3 (Yang et al., 2025)

5https://huggingface.co/
collections/naver-hyperclovax/
hyperclova-x-seed-6808cf1affbfdfeed0481887

<sup>6</sup>https://tech.kakao.com/posts/706

Models	CO	NA	IN	CGA	F-score	
Korean Community LLMs						
EXAONE 3.5 2.4B	7.3	27.9	64.8	10.1	8.5	
<b>EXAONE 3.5 7.8B</b>	15.3	15.3	69.4	18.1	16.6	
EXAONE 3.5 32B	28.8	8.4	62.8	31.4	30.1	
HCX SEED 0.5B	3.8	9.7	86.5	4.2	4.0	
HCX SEED 1.5B	5.4	21.0	73.6	6.8	6.0	
HCX SEED 3B	8.0	6.9	85.1	8.6	8.3	
HCX SEED 14B	33.7	7.8	58.5	36.6	35.1	
kanana 1.5 2.1B	15.5	14.6	69.9	18.1	16.7	
kanana 1.5 8B	29.3	3.2	67.5	30.3	29.8	
Multilingual LLMs Supporting Korean						
gemma 3 1B	2.4	3.6	94.0	2.5	2.4	
gemma 3 4B	7.9	1.9	90.2	8.1	8.0	
gemma 3 12B	18.7	0.5	80.8	18.8	18.7	
gemma 3 27B	29.5	0.6	69.9	29.7	29.6	
Llama 3.1 8B	5.7	21.8	72.5	7.3	6.4	
Llama 3.1 70B	19.2	15.3	65.5	22.7	20.8	
Qwen3 0.6B	1.0	20.0	79.0	1.2	1.1	
Qwen3 1.7B	2.2	2.1	95.7	2.2	2.2	
Qwen3 4B	4.5	3.0	92.5	4.6	4.6	
Qwen3 8B	7.0	1.7	91.3	7.1	7.1	
Qwen3 14B	10.8	2.2	87.0	11.0	10.9	
Qwen3 32B	11.1	1.9	87.0	11.3	11.2	

Table 1: Results of different models on KoSimpleQA. For metrics, **CO**, **NA**, **IN**, and **CGA** denote "Correct", "Not attempted", "Incorrect", and "Correct given attempted", respectively. HCX denotes HyperCLOVA X.

#### 3.1.2 Sampling Parameters

For all of the experiments, we generated answers with temperature = 1.0,  $top_p = 1.0$ , and  $max\_tokens = 2,048$ , following the parameters released in the SimpleQA evaluation code<sup>7</sup>.

#### 3.2 Main Results

We provide the performances of baselines on KoSimpleQA in Table 1. In line with commonly reported scaling behavior (Kaplan et al., 2020), performance scales with model size within the same LLM family. However, when comparing across different families, we observe a clear distinction: Korean community LLM families outperform multilingual LLM families supporting Korean. Notably, when comparing the largest models within each family, despite the multilingual group including the largest model, none surpass Korean community models.

However, as shown in Figure 3, multilingual models outperform Korean community models on original SimpleQA. This contrast indicates that KoSimpleQA captures aspects that are not eval-

<sup>&</sup>lt;sup>7</sup>https://github.com/openai/simple-evals

Models	CO	NA	IN	CGA	F-score
EXAONE Deep 2.4B	0.1(-7.2)	88.2(+60.3)	11.7(-53.1)	0.8(-9.3)	0.2(-8.3)
EXAONE Deep 7.8B	3.4(-11.9)	16.7(+1.4)	79.9(+10.5)	4.1(-14.0)	3.7(-12.9)
EXAONE Deep 32B	16.0(-12.8)	5.6(-2.8)	78.4(+15.6)	16.9( <b>-14.5</b> )	16.5(-13.6)
HCX SEED 14B think	34.5(+0.8)	16.2(+8.4)	49.3(-9.2)	41.2(+4.6)	37.5(+2.4)
Qwen3 0.6B think	1.0(0.0)	15.9(-4.1)	83.1(+4.1)	1.2(0.0)	1.1(0.0)
Qwen3 1.7B think	3.0(+0.8)	6.8(+4.7)	90.2(-5.5)	3.2(+1.0)	3.1(+0.9)
Qwen3 4B think	4.3(-0.2)	6.6(+3.6)	89.1( <b>-3.4</b> )	4.6(0.0)	4.4(-0.2)
Qwen3 8B think	8.8(+1.8)	7.3(+5.6)	83.9(-7.4)	9.5(+2.4)	9.1(+2.0)
Qwen3 14B think	13.4(+2.6)	5.3(+3.1)	81.3(-5.7)	14.1(+3.1)	13.8(+2.9)
Qwen3 32B think	12.7(+1.6)	7.8(+5.9)	79.5( <b>-7.5</b> )	13.8(+2.5)	13.2( <b>+2.0</b> )

Table 2: Results of different reasoning models on KoSimpleQA. The numbers in parentheses denote the performance differences relative to each corresponding base instruct model.

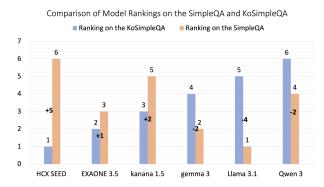


Figure 3: The rankings of the largest models in each LLM family on SimpleQA and KoSimpleQA.

uated by existing benchmarks such as SimpleQA. The divergence further suggests that models trained predominantly on less-resourced languages may be systematically underestimated under benchmarks centered on high-resource languages. By providing an evaluation grounded in Korean cultural and linguistic knowledge, KoSimpleQA offers a more accurate and balanced assessment of such models.

# 3.3 Behavior of Reasoning Models on KoSimpleQA

Several of the baselines provide an explicit thinking mode, and we evaluated these models on KoSimpleQA with their thinking mode activated. Note that for EXAONE, the base instruct model itself does not include a thinking mode; the reasoning ability was introduced through an additional finetuning step (Research et al., 2025). Another implementation detail is that whenever a model failed to produce a final assistant response—continuing to "think" until reaching the maximum token limit—we marked the instance as *not attempted*.

EXAONE Deep exhibited a substantial drop in performance compared to its base instruct version.

The difference was large across most metrics, suggesting that catastrophic forgetting may have occurred, likely compromising factual reliability for reasoning-specific behavior. In contrast, other models with built-in reasoning capabilities either maintained or improved their overall performance.

A particularly notable trend is that the rate of *not* attempted responses increased sharply, while correct responses were largely preserved or slightly improved. This pattern indicates that thinking mode makes models less likely to guess when uncertain and better able to retrieve or elicit latent knowledge. The improvement in not attempted likely stems from models getting stuck in extended thinking loops, leading them to abstain rather than hallucinate. Meanwhile, the gains in correct responses suggest that reasoning can indeed help models arrive at factual answers. As shown in Appendix B, a similar phenomenon was observed on the original SimpleQA benchmark, reinforcing the view that reasoning-oriented generation can positively influence general factual QA performance.

#### 4 Conclusion

In this work, we introduced KoSimpleQA, a benchmark for evaluating factuality in Korean cultural contexts. Our evaluation across diverse LLMs revealed that current models still struggle with factual accuracy in Korean, and performance rankings diverge notably from English benchmarks, underscoring the benchmark's cultural relevance. Moreover, our analysis of reasoning models showed that reasoning can both enhance factual precision and promote abstention when uncertain. We hope KoSimpleQA will serve as a foundation for developing more culturally grounded and factually reliable language models.

#### Limitations

KoSimpleQA shares a main limitation of SimpleQA-style benchmarks, namely that they assess factuality only under constrained settings—short, fact-seeking questions with single, verifiable answers. While this design ensures evaluation precision, it does not capture whether the ability to generate factual short answers translates to producing longer, fact-rich responses. Bridging this gap remains an open direction for future research.

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#### A Related Work

SimpleQA (Wei et al., 2024) pioneered the direct evaluation of factuality through short, unambiguous questions that are both challenging and easy to grade. While it has become a standard reference for English models, its questions are largely rooted in Anglophone cultural knowledge, which limits applicability beyond that context.

Chinese SimpleQA (He et al., 2024) adapted the format to Chinese cultural and linguistic contexts. Their results showed that cultural grounding can substantially shift model rankings, underscoring the need for language-specific benchmarks.

**KoSimpleQA** continues this line of work by extending SimpleQA-style evaluation to Korean. In addition to filling the cultural gap, we complement prior benchmarks with an analysis of reasoning-oriented models in factual QA, offering additional insight into how reasoning affects factual reliability.

## **B** Results on SimpleQA

Here we report the results of base instruction models and reasoning models on SimpleQA in Table 3 and 4, respectively.

Models	CO	NA	IN	CGA	F-score	
Korean Community LLMs						
EXAONE 3.5 2.4B	1.4	36.0	62.6	2.2	1.7	
EXAONE 3.5 7.8B	2.5	33.0	64.5	3.7	3.0	
EXAONE 3.5 32B	5.0	34.3	60.7	7.6	6.1	
HCX SEED 0.5B	0.6	10.9	88.5	0.7	0.6	
HCX SEED 1.5B	0.4	56.2	43.3	1.0	0.6	
HCX SEED 3B	1.6	22.9	75.5	2.1	1.8	
HCX SEED 14B	2.4	61.7	35.8	6.3	3.5	
kanana 1.5 2.1B	1.7	17.7	80.6	2.0	1.8	
kanana 1.5 8B	3.6	8.1	88.3	3.9	3.7	
Multilingual LLMs Supporting Korean						
gemma 3 1B	1.9	2.1	96.0	2.0	1.9	
gemma 3 4B	4.2	0.3	95.5	4.2	4.2	
gemma 3 12B	5.5	0.3	94.2	5.6	5.6	
gemma 3 27B	9.5	0.3	90.2	9.5	9.5	
Llama 3.1 8B	1.7	89.0	9.4	15.1	3.0	
Llama 3.1 70B	12.9	65.3	21.8	37.1	19.1	
Qwen 3 0.6B	1.0	5.8	93.2	1.1	1.0	
Qwen 3 1.7B	2.1	3.8	94.2	2.1	2.1	
Qwen 3 4B	3.1	3.7	93.1	3.2	3.2	
Qwen 3 8B	4.0	3.9	92.1	4.2	4.1	
Qwen 3 14B	5.2	4.5	90.4	5.4	5.3	
Qwen 3 32B	5.7	1.6	92.7	5.8	5.8	

Table 3: Results of different models on SimpleQA

Models	CO	NA	IN	CGA	F-score
EXAONE Deep 2.4B	0.2(-1.2)	91.5(+55.5)	8.3(-54.3)	2.7(+0.5)	0.4(-1.3)
EXAONE Deep 7.8B	0.5(-2.0)	80.7(+47.7)	18.8(-45.7)	2.5(-1.2)	0.8(-2.2)
EXAONE Deep 32B	1.5(-3.5)	84.5(+50.2)	14.0(-46.7)	9.7(+2.1)	2.6(-3.5)
HCX SEED 14B think	3.6(+1.2)	39.3(-22.4)	57.1(+21.3)	5.9(-0.4)	4.5(+1.0)
Qwen 3 0.6B think	1.3(+0.3)	8.1(+2.3)	90.7(-2.5)	1.4(+0.3)	1.3(+0.3)
Qwen 3 1.7B think	2.2(+0.1)	9.6(+5.8)	88.2(-6.0)	2.5(+0.4)	2.4(+0.3)
Qwen 3 4B think	3.0(-0.1)	15.8(+12.1)	81.2(-11.9)	3.6(+0.4)	3.3(+0.1)
Qwen 3 8B think	4.2(+0.2)	21.1(+17.2)	74.7(-17.4)	5.3(+1.1)	4.7(+0.6)
Qwen 3 14B think	5.2(0.0)	12.8(+8.3)	81.9(-8.5)	6.0(+0.6)	5.6(+0.3)
Qwen 3 32B think	5.0(-0.7)	18.8(+17.2)	76.2( <b>-16.5</b> )	6.1(+0.3)	5.5(-0.3)

Table 4: Results of different reasoning models on SimpleQA